A task-based approach to labor market outcomes: Income, jobs, and satisfaction

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Chapter 1

Introduction

Since the highly influential paper by Autor et al. (2003), task compositions of occupations and their effects on changes in the wage structure have become a field of major interest within the economic literature. Task compositions of occupations have changed drastically over the last 30 years and substantially altered the demand for skills and human capital. Therefore, Autor et al. (2003) introduced the task-based view in the literature on labor markets.

Although most recently researchers such as Autor et al. (2003) and Spitz-Oener (2006), rely on the task-based view to explain the increasing demand for high educated workers and and the steadily rising income inequality, researchers did not yet answer whether different types of tasks affect labor market outcomes such as job choices, unemployment or even entire individual careers.

Until today most available data sets contain rather broad classification of individual's industries or occupations. Therefore, researchers face difficulties to provide empirical evidence for the influences of the task-based view on most labor market outcomes. Yet even if jobs and occupations are in particular descriptions for different bundles of tasks, the tasks themselves influence labor market outcomes and the classification according to jobs and occupations is far to broad to describe many labor market phenomena. Therefore, we argue that the tasks-based view is a fruitful concept to explain and account for many phenomena in the labor market. As workers careers are the main incentive for human capital investments and economic growth, investigating the task-based view in relation to a variety of labor market outcomes is worthy research which enables us to provide novel and far reaching policy implications.

To fill the gap in the existing literature, this dissertation investigates the relationship between occupational task compositions and different types of individual labor market outcomes, which help to gain novel insights into labor market phenomena that were not well explainable without the consideration of the tasks based view.

The second chapter of this dissertation links the task-based view to the literature on human capital depreciation. In particular, we analyze the relationship between occupational task compositions and human capital depreciation. As former empirical studies show that technological changes cause human capital depreciation, researchers are aware that not only the amount of human capital investments but also the time of those investments matters to the individual. However, these papers do not consider that workers performing different types of tasks suffer to different extends from human capital depreciation.

Therefore, we introduce the task-based view in the literature on human capital depreciation by investigating human capital depreciation for individuals who perform different kinds of tasks in their jobs. In particular, we distinguish between two broad task categories. First, we define the category of knowledge-based tasks, as tasks that are closely related to certain technologies or the general stock of knowledge available to society. One example for such tasks is writing computer programs, as programming depends strongly on technological development. Second, we define the category of experience-based tasks, as tasks that demand personal characteristics and can be improved by more experience but are not closely attached to a certain kind of technology or the general stock of knowledge. An example of such tasks is negotiating with customers or business partners. Individuals surely might be able to improve their negotiating skills, but these skills should not depend too much on ongoing technological changes. We show in our empirical investigation that individuals with comparably high percentages of knowledge-based tasks have higher rates of human capital depreciation than individuals with comparably high percentages of experience-based tasks. The results indicate that ignoring the heterogeneity of individuals' job contents in the analysis of human capital depreciation might lead to misleading policy implications. In particular, technological changes do not only alter the demand for low- and high-skilled workers but also affect the productivity of different types of skills over a workers life cycle. Therefore, our main contribution to the literature is to show that human capital depreciation is highly heterogeneous across workers performing different tasks. Thus the task-based view helps us to understand why this heterogeneity arises in the first place.

The third chapter of this dissertation continues to investigate the relation between tasks bundles and income. First, we link the task based view to the literature on job displacement and investigate income losses of individuals that perform different types of tasks. Second, this chapter investigates displacement losses under different forms of wage bargaining systems within one country. For this purpose, we estimate income losses of Danish workers in different occupations that were displaced at different points in time between 1980 and 2004—a period in which Denmark underwent a substantial decentralization of it's wage bargaining system.

We find that displacement losses increased substantially after the introduction of the flexible wage bargaining system. Moreover, we find that displacement losses of commercial apprenticeship graduates depend substantially on the wage bargaining system but displacement losses of manufacturing workers do not. In other words, commercial workers suffer rather small displacement losses under a rigid wage bargaining system but their displacement losses increased substantially after the introduction of the flexible wage bargaining system. In contrast the pattern of the displacement losses of manufacturing workers remained rather similar under both the flexible and the rigid wage bargaining system. One possible explanation for this difference is the nature of the workers human capital. Particularly because manufacturing workers can be expected to have much more specific human capital investments their displacement losses are mostly driven by specific human capital losses and do not depend substantially on the nature of the wage bargaining system.

Therefore, the contributions of this chapter are twofold. First, by showing a relation between wage flexibility and displacement losses, we provide a new insight of why displacement losses differ so substantially between Europe with it's mostly rigid wage formation process and the U.S. with it's flexible wage bargaining system. Second, by showing that the relation between displacement losses and wage flexibility differs substantially for workers with different types of human capital, we show that displacement losses do dependt on the workers task contents.

Human capital and income are not the only labor market outcomes that are affected by job contents and different forms of tasks. Individuals choose their jobs because they prefer or dislike certain kinds of tasks. Some individuals might gain utility by performing tasks they like, whereas other individuals suffer because they have to perform task they do not like. However, preferences are not randomly distributed within the labor force. In particular, social stereotypes about individual characteristics such as gender or ethnicity are likely to determine individuals' preferences for jobs and tasks.

Building on this idea recent theoretical papers incorporate the sociological concept of identity into classical utility frameworks. These papers investigate how stereotypes affect worker's utility and influence labor market outcomes such as job choices and other career decisions (e.g. Akerlof and Kranton (2000)). The theoretical literature argues that the individuals identity is determined by gender-specific stereotypes leading utility maximizing individuals to choose jobs that are socially acceptable rather than choosing the best paid jobs. Consequently, such theories might help to understand the persistence of gender segregation in the labor market. Nevertheless, because of the lack of empirical evidence on the relationship between gender-specific stereotypes and utility it remains difficult to access the validity of these theories.

Therefore, we link the task-based view to the literature on job satisfaction by investigating the relation between individual utility—measured as job satisfaction—and different task bundles that are linked to gender-specific stereotypes. In particular, the third chapter investigates a sub-topic of the literature on jobs satisfaction by investigating the relationship between stereotypical task contents and gender-specific job satisfaction.

We use a special dataset allowing us to link the concept of gender stereotypes, tasks and job satisfaction. The chapter shows that women are less satisfied with their jobs—in particular with their work climate—if performing tasks associated with male stereotypes. In contrast, men are less satisfied with their jobs if performing tasks related to female stereotypes.

This dissertation contributes to the literature on job satisfaction by showing, with a big representative data set, that gender-specific stereotypes influence job satisfaction. Moreover, this dissertation provides the first large-scale evidence on a theoretical paper that introduces the sociological concepts of identity and social stereotypes in an economic framework (Akerlof and Kranton; 2000). Additionally, we contribute to the literature on gender segregation by showing that choosing socially acceptable jobs rather then the best paid jobs might be a utility maximizing strategy for individuals.

In the final chapter, we draw conclusions by synthesizing the results from all three studies and present policy implications.

Chapter 2

Skill obsolescence, vintage effects and changing tasks

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2.1 Introduction

This chapter is our first contribution in investigating the relation between different types of tasks and labor market outcomes. In particular, we investigate the value of human capital for individuals performing different types of tasks and show how the value of these tasks changes over an individual's span of life. As the most intuitive value of human capital are ernings, this chapter investigates experience earnings profiles for individuals that perform different sets of tasks.

Human capital is no doubt one of the most important factors for future economic growth and well-being, but human capital is also prone to become obsolete over time. Skills that have been acquired at one point in time may perfectly match the skill requirements at that time but may become obsolete as time goes by. The more innovative an economy is, the more likely it is that particular technological or methodological skills will become obsolete.

Spitz-Oener (2006) showed that the composition of tasks demanded by different occupations has changed considerably over the last decades. Specifically, Spitz-Oener (2006) showed that routine tasks manual tasks were replaced by non-routine cognitive or analytical tasks. However, independently of whether tasks are routine or non-routine different types of tasks might suffer in different ways of human capital depreciation. In particular, we argue that two types of tasks must be distinguished: knowledge-based tasks and experience-based tasks. We define knowledge-based tasks as tasks depending strongly on the general stock of technological knowledge available to society, whereas experienced-based tasks are defined as tasks demanding personal characteristics that can be improved by gaining more and more experience. In contrast to Spitz-Oener (2006), both of our task categories may contain routine and non-routine tasks. The major novelty of our categorization is that the human capital of people performing knowledge-based tasks strongly suffers from depreciation, whereas the human capital of individuals performing experience-based tasks does not. This is mainly because the general stock of technological knowledge available to a society at a given point in time is changing and rising. Therefore, technologies and work processes are changing. If certain human capital is strongly related to older technologies or work processes, it becomes worthless with the disappearance of the technologies and processes. As knowledge-based tasks by definition depend on the actual stock of technological knowledge we argue that individuals performing mainly knowledge-based tasks in their jobs should suffer more from skill obsolescence than individuals performing mainly experience-based tasks which are timeless and comparatively independent from actual technologies. Therefore, we extend the study of Spitz-Oener (2006) by investigating whether the human capital depreciates differently for workers performing different types of tasks with different skill requirements over a period of more than twenty years.

We investigate this relationship by observing different influences of task combinations on individual incomes. In order to study such effects, we need a database with detailed information on tasks that people perform at the workplace over a long time span. Therefore, we use the four waves of the so-called BIBB/IAB Qualification and Career Survey because it not only deeply specifies the tasks individuals perform in their jobs, but also covers a time span of more than twenty years, which is a prerequisite to studying the above-mentioned vintage effects.

Making use of extended Mincer type earnings regressions (similar to an approach developed by Neuman and Weiss; 1995), we find the following: workers performing different types of tasks are affected differently by skill obsolescence. In more detail workers face greater skill obsolescence whenever the share of knowledge-based tasks is high in comparison to the share of experience-based tasks. These results provide novel insights in the way of looking on experience earnings profiles and extend the literature on skill obsolescence since previous literature distinguished only between differences in the obsoleteness of various groups of workers (for example, with different educational backgrounds), but not between differences in obsoleteness depending on the types of tasks a person performs.

The rest of the chapter is organized as follows. In chapter 2.2, we present previous literature and our own theoretical considerations in more detail. In chapter 2.3, we present our estimation strategy. In chapter 2.4, we describe the data. Chapter 2.5 follows with the results, and chapter 2.6 concludes the article.

2.2 Literature and theory

Rosen (1975) and Ben-Porath (1967) were among the first to study depreciation or obsolescence due to technological progress. They point out that human capital loses value because it is related to technologies that are no longer used. Workers of recent vintages are beneficiaries of new technologies as they grew up with recent knowledge about the technology and were adapted to it during school, further education or training. Thus, younger workers can be more productive than workers of older vintages if the older workers do not continue investing in recent human capital. As soon as older technologies are no longer used, skills connected to them become obsolete. As Rosen (1975) argues more comprehensively, some (technological) knowledge may turn out to be incorrect or less general than it was supposed to be in former times.

The empirical literature investigates skill obsolescence or depreciation using different approaches (for an overview, see De Grip and Van Loo; 2002). Some studies focus on subjective measures or certain labor market outcomes, such as unemployment or the transition from education to work. Ludwig and Pfeiffer (2005), for example, show, by using a subjective measure, that human capital accumulated during vocational training is confronted with a steadily rising rate of depreciation. However, apart from that, most studies focus on wages. While some try to measure the rate of depreciation exactly, such as Arrazole and de Hevia (2004) or Groot (1998), others focus more on the detection of vintage effects or depreciation in general (Neuman and Weiss; 1995; Weiss; 1978).

Thus, the literature supports the theory that workers who entered the labor market in earlier years and have acquired older skill vintages can be expected to have less up-to-date knowledge than workers entering more recently and holding more recent skill vintages. On one hand the appearance of new technologies makes skills become obsolete if they are attached to older technologies. On the other hand older workers invest less time in accumulating human capital, accumulate less of the steadily growing stock of recent technological knowledge and, therefore, cannot countervail the negative effects of human capital depreciation.

However, we argue that obsolescence due to external changes, such as technological progress will not affect every skill set equally. The rate of skill obsolescence rather depends on the tasks a worker must perform or the objectives he is confronted with in his working life. We argue that two types of tasks must be distinguished, which we will call knowledge-based tasks and experience-based tasks throughout the rest of the paper.

We argue that knowledge-based tasks depend strongly on the actual stock of technological knowledge in a society and therefore, we expect people performing mainly these kinds of tasks to strongly suffer from depreciation and skill obsolescence. Writing computer programs, for example, depends strongly on technological developments in this field. Currently, for instance, many business applications are written in .NET or Java. Younger workers who are trained in these programs have productivity advantages in comparison to older workers who grew up with Fortran or Pascal.

In contrast, we define experience-based tasks as tasks depending on personal factors and abilities that grow with individual experience. Selling or negotiating are two examples for these kinds of tasks. These tasks demand a good sense for human behavior or certain personal characteristics such as sympathy or self esteem and depend less on technological knowledge. Thus, we expect them to suffer less from depreciation due to technological change. Instead, it seems reasonable to assume that more experienced workers (older vintages) have even an advantage in performing these kinds of tasks.

So far we only considered the depreciation due to external factors such as the technological development. But skills could also become obsolete due to internal factors; i.e. simply due to the aging of individuals and this aging affecting their individual productivities. This kind of skill depreciation is called internal depreciation and the psychological and medical literature can provide additional helpful insights on this. It distinguishes between different kinds of intelligence. On the one hand, the concept of fluid intelligence refers to abilities such as the fast processing of information or the ability to understand abstract concepts. On the other hand, the concept of crystalline intelligence refers to skills based on experience and social competence, as well as the ability of ambivalence. They argue that fluid intelligence depreciates due to biological aging from thirty years onwards. Crystalline intelligence, however, does not suffer from depreciation due to aging (Sternberg; 2005; Baltes et al.; 2005; Compton et al.; 2003) .

One can argue that the handling of technologies or technology related knowledge requires abilities such as processing information or understanding abstract concepts. Hence, fluid intelligence is probably more important to perform knowledge-based tasks properly than experience based tasks. In contrast one can argue that experience-based tasks demand abilities such as social competence and therefore particularly benefit from crystalline intelligence. Thus, the evidence from psychological literature on aging supports our view that skill obsolescence is larger for workers performing mainly knowledge-based tasks than for workers performing mainly experience-based tasks. Moreover, as crystalline intelligence is important to perform experience-based tasks one can conclude that older workers should even benefit from focusing on these kinds of tasks.

In sum, we can conclude that the skills needed to perform knowledge-based tasks should suffer more from skill obsolescence then the skills needed to perform experience-based tasks. In fact, one could expect that the latter improve with experience. In the following, we try to measure this effect indirectly by applying an idea from Neuman and Weiss (1995) to experience earnings profiles in cross sectional data.

2.3 Estimation strategy

In this section, we show what we can learn about human capital depreciation from estimated experience earnings profiles. Therefore, we follow Neuman and Weiss (1995) and Ramirez (2002) by applying an idea from Mincer (1974) to cross sectional data. The main focus of our investigation will be the year of experience at which earnings profiles peak. In detail, we look for the earnings peaks for different groups of workers performing different kinds of tasks.

To clarify our approach we give a short overview of the classical Mincer model with depreciation. Mincer (1974) stated that an individual's earnings capacity E_j after j years in the labor force will be approximately

$$\ln E_j = E_0 + \sum_{j-1}^{t=0} r_t k_t \tag{2.1}$$

E_0 is the earnings capacity when the individual starts working, and r_t is the rate of return in on-the-job training; $k_t = \frac{C_t}{E_t}$ is the ratio of investment in on-the-job training (C_t) to gross earnings (E_t), and it is assumed that $k_t \leq 1$ and decreases over time. Equation (2.1) represents the so-called standard Mincer model. However, Mincer (1974) himself expanded this model by incorporating a rate of depreciation δ_t . Thus, equation (2.2) follows:

$$\ln E_j = E_0 + \sum_{j-1}^{t=0} (r_t k_t^* - \delta_t) \tag{2.2}$$

Whereby k_t^* is now the ratio of gross investment with C_t^* . In empirical data we are able to observe net earnings rather than the earnings capacity. If Y_j are the net earnings at time $t = j$, one can show that:

$$\ln Y_j = \ln Y_{j-1} + \ln(1 + r_{j-1} k_{j-1}^* - \delta_{j-1}) + \ln(1 - k_j^*) - \ln(1 - k_{j-1}^*) \tag{2.3}$$

Thus, earnings will peak when the right hand side of equation (2.3) equals the left hand side. Hence, earnings peak if we have:

$$\delta_{j-1} = (1 + r_{j-1})k^*_{j-1} - k^*_j \tag{2.4}$$

As k^*_j is assumed to be strictly linear and decreasing, equation (2.4) indicates that earnings will peak earlier if the rate of depreciation is higher. The distance between $k^*_{j-1} - k^*_j$ is bigger at earlier stages of a worker's career. Like Neuman and Weiss (1995) and Ramirez (2002), we argue that the rate of depreciation is not equal for everyone. In contrast to Neuman and Weiss (1995), we are not interested in understanding how skill obsolescence works for the human capital of different education groups. Instead, as previously mentioned, we argue that skill obsolescence depends on the tasks a worker performs. Hence, we have where kbt denotes the amount of knowledge-based tasks and ebt denotes the amount of experience-based tasks in an individual's job.

Thus, from our theory we expect the rate of depreciation to be higher for people performing jobs demanding a higher amount of knowledge-based tasks given the amount of experience-based tasks. Thus, $\frac{\partial\delta}{\partial kbt} > 0$. Therefore, given the amount of experience based tasks, the earnings functions should peak earlier the higher the amount of knowledge-based tasks. As we expect the reverse to be true for experience-based tasks, we have $\frac{\partial\delta}{\partial ebt} < 0$.

To prove our hypotheses, we apply the following extended Mincer type earnings function:

$$\begin{aligned} \ln y_i = \beta_0 + \beta_1 exp_i + \beta_2 exp_i^2 + \beta_3 kbt_{ij} + \beta_4 kbt_{ij} * exp_i + \beta_5 ebt_{ij} \\ + \beta_6 ebt_{ij} * exp_i + X_i\beta_7 + \varepsilon_i \end{aligned} \tag{2.5}$$

$\ln y_i$ stands for the logarithm of the observed net earnings of individual i; exp_i and its squared term are the years of labor market experience; β_1 and β_2 are the respective coefficients. X_i is a matrix containing further controls, such as schooling, professional status, gender and firm size. β_7 is the respective coefficient vector. ε_i is assumed to be a normal distributed error term with mean zero. As we are interested in measuring the effects of certain task compositions on experience earnings profiles, we extended the classical Mincer model by kbt_{ij}, a variable measuring the average share of all knowledge-based tasks observable in the data for individual i's job j, and by ebt_{ij} , the average share of all experience-based tasks observable in the data for individual i's job j. Moreover, we interacted the variables kbt_{ij} and ebt_{ij} with the experience variable exp_i. β_3 to β_6 are the respective coefficients. Thus, as we expect the earnings profile to peak earlier for an increasing amount of knowledge-based tasks (given the amount of experience-based tasks) the coefficient β_4 should be negative. In the same way, the coefficient β_6 should be positive as we expect the earnings profiles to peak later if the amount of experienced-based tasks is large.

In the language of Mincer (1974), equation (2.6) gives the experience value at which earnings peak (i.e., the derivative of (2.5) with respect to exp_i solved for exp_i). The left hand side of (2.6) will decrease as *kbt* rises if β_4 is negative and increase if *ebt* rises and β_6 is positive (note that in Mincer regressions β_1 is expected to be positive and β_2 is expected to be negative).

$$exp_i = f(\beta_1, \beta_2, \beta_3, \beta_4) = \frac{-(\beta_1 + \beta_4 kbt + \beta_6 ebt)}{2\beta_2} \tag{2.6}$$

However, one could also give two more intuitive interpretations for the expected regression results.

First, if β_4 in (2.5) is negative, it indicates that the marginal rate of return for experience decreases faster if the share of knowledge-based tasks is higher, whereas a positive β_6 indicates that the marginal rate of return for experience decreases slower if the share of experience-based tasks is higher. Thus, under the assumption of equal investments in human capital, the value of one year of human capital investments decreases faster for people performing a high share of knowledge-based tasks then for people performing a comparative high share of experienced-based tasks. This indicates a higher rate of depreciation for people performing mainly knowledge-based tasks in their jobs.

Second, one could give an alternative interpretation of the maximum of experience earnings profiles in cross sections. The second interpretation considers the fact that it is not possible to follow individuals over time if we look on cross-sectional evidence. Specifically, as we observe individuals with different amounts of work experience at one point in time, an early peak indicates that many individuals with relatively short working careers earn more than individuals with longer careers. Thus, one could argue, as individuals with shorter careers usually have more recent human capital then individuals with longer careers, that there is a taste for fresh human capital in the labor market. In other words, individuals with longer careers and a high amount of human capital suffer due to skill obsolescence and earn less than their younger colleagues. This interpretation is more in line with a recent model by Laing et al. (2003).

2.4 Data

For our empirical investigation, we used data from the Qualification and Career Survey. This survey is carried out by the German Federal Institute for Vocational Training (Bundesinstitut für Berufsbildung) and the research Institute of the Federal Employment Service (Institut für Arbeitsmarkt- und Berufsforschung). It sampled a representative group of the German workforce in 1979, 1985/86, 1991/92 and 1998/99. Each sample contains around 30,000 observations.

We only cover people between the ages of 18 and 65 having no more than 45 years of experience. We excluded individuals from East Germany (because they are not observable in every wave), foreigners, the unemployed, self-employed workers and individuals working less than 35 hours per week. In addition, we excluded workers with implausible high or low wages by dropping one percent of people with the highest and one percent of people with the lowest wages. These constraints result in 15,278 observations in 1979, 15,330 observations in 1985/86, 13,808 observations in 1991/92, and 11,871 observations in 1998/99.

The underlying data set refers to tasks that people have to perform to properly do their jobs. Hence, people had to choose these tasks from a given list. As mentioned in the second section, we distinguished between two types of tasks. The first category refers to knowledge-based tasks and the second to experience-based tasks. These categories were constructed as presented in Appendix A.2 to A.5 for each wave.

Thus, knowledge-based tasks are all tasks for which it can be assumed that they depend strongly on a given type of technical knowledge at a certain point in time. As an example one can take "repairing machines, equipment, etc.". It is obvious that a person has to have knowledge of the machine's technology. If this technology changes, the worker's abilities will no longer fit with the skill requirements to repair these machines. Thus whenever technology is involved that is not timeless, we expect to find strong skill obsolescence effects. However, this category does not only include technology in the sense of machinery, or hard- and software, but also for example legal or institutional regulations which also might strongly change over time. An example that one could think of are changing collective agreements, labor law or environmental law: the rules that have to be met at one point in time may be different from the rules that have to be met at another point in time. Thus, the particular knowledge from one time period may be completely obsolete in a later period. Moreover, these tasks demand analytical skills and therefore fluid intelligence which we also relate to knowledge-based tasks. A complete overview of knowledge-based tasks in comparison to experience-based tasks is given in table A.2 to A.5 in the appendix. We expect all tasks on the right side of the tables in A.2 to A.5 to be affected quite strongly over time by external changes in the stock of technological knowledge. In contrast, we argue that all tasks on the left side of the tables in A.2 to A.5 are not affected by external changes in the stock of technological knowledge. Instead, the tasks on the left side depend more on personal factors which may even increase over time due to increased experiences. Thus, we do not expect strong depreciation effects for these types of tasks.

Compared to Spitz-Oener (2006) who also suggested a separation of different tasks based on the same variables of the BIBB/IAB data set, our categories are different in two ways. First, we use a more complete set of tasks in the single waves then she did. Since we were not interested in observing changes in task combinations from wave to wave, we were not faced with the same restrictions like Spitz-Oener (2006). Because our analysis uses each of the single waves separately we were not forced to use only comparable tasks in each of the waves. Thus, we decided to incorporate more tasks in our categories even if they were not observable in every wave. Second, our definition criterion reference is quite different because we were interested in the distinction between task depending on technological knowledge and tasks depending on personal factors and communication skills. For example, in her paper tasks such as equipping machines are considered to be routine manual tasks. In our paper we argue they are knowledge-based tasks because workers performing these tasks have to deal with potentially changing technologies. The question whether a task at a given point in time is routine or non-routine is not important to us; for our analysis it is only important whether for a given task at a given time the job requirements are expected to be the same as for a task at a future point in time.

In addition, to consider the fact that task sets differ quite widely between the single cross sections, we will calculate two versions of the measure to check the robustness of our results.

First, we created a measure in a similar fashion to Spitz-Oener (2006) (with different categorization). Thus, we divided the number of activities that an individual performs in each category (knowledge based tasks/experience based tasks) by the total number of observable tasks in that category. Afterwards, we calculated the average of this task measure for each of the 83 job categories listed in Appendix A.6. This was done for every wave separately as task sets observable in each wave differ strongly. Thus, every job has four different task measures for both categories (one for each wave).

A second measure was created by pooling the sample of all four waves and calculating an overall average of the first measure for each occupation and task category, which is constant over all waves. Hence, there is just one pooled value that differs for each job and category but is the same in each wave.

To give an example of the first measure, we observe that mechanics performed on average around 6 percent of knowledge based tasks and 2 percent of experience based tasks in 1979. For 1985/86 we have 24 percent and 6 percent, for 1991/92 we have 25 and 6 and for 1998/99 we have 52 and 37 percent. Note that the values differ quite widely and are not comparable over time as the questionnaires were different in every wave. However, for the second measure, mechanics perform on average 24 percent of all observable knowledge based tasks and around 9 percent of all observable experience based tasks.

The first approach has the advantage that we can test whether our expectations hold independent of the fact that the tasks we are able to observe in every wave differ quite strongly. Nevertheless, it has the drawback that we may measure different effects in every wave. The second approach ensures that we measure a similar effect in every wave by considering the average of all observable tasks weighted by the individuals performing the respective jobs in every wave. The drawback of the second approach is that we have to assume that the average task combinations did not change within jobs over time. The measures will be used as indicators for and of equations (2.5) and (2.6).

For y_i we use monthly wages. The experience measure exp_i was directly obtained from the survey. Moreover, we added certain controls in X_i. We used a set of dummies corresponding to the degrees in the German education system as variables for the level of general education. Thus, we created a dummy taking the value of one whenever an individual holds neither an apprenticeship degree nor a university degree (low education). A second dummy is one if the individual holds an apprenticeship degree (medium education), and a third is one for university graduates (high education). Moreover, we used a dummy for gender, taking the value of 1 if the person is female and 0 otherwise. Further controls were added for the professional status of the worker, including dummies for unskilled, blue collar workers (skilled), foremen, white collar workers and civil servants. Firm size dummies were also included in the regressions. Descriptive statistics on all explanatory variables can be found in Appendix A.1.

2.5 Results

2.5.1 Descriptive statistics

In Table 2.1, we present some detailed descriptive statistics of our task measures for the pooled sample. In the descriptive statistics, we will only refer to the pooled sample as the statistics give qualitatively the same results if we look on each wave separately.

Table 2.1: Descriptive statistics for index of knowledge and experience based tasks

Average percentage of all performed knowledge-based tasks (*kbt*) by category			
Professional Status:			
Unskilled	Blue Collar	White Collar	Civil Servant
10.26	18.92	23.43	16.60
Education:			
Low education	Medium Education	High Education	
9.31	16.94	25.63	
Gender:			
Female	Male		
10.96	19.1		

Average percentage of all performed experience-based tasks (*kbt*) by category			
Professional Status:			
Unskilled	Blue Collar	White Collar	Civil Servant
3.87	7.02	19.94	25.59
Education:			
Low education	Medium Education	High Education	
6.624	16.92	33.99	
Gender:			
Female	Male		
18.984	16.05		

Note: All data are drawn from the BIBB/IAB Strukturerhebung 1979-1998/99.

In the first and second column we examine how the tasks are distributed across different levels of professional status. Thus, the first row in the third column tells us, for example, that unskilled workers perform around 10 percent of all observable knowledge-based tasks and only around 4 percent of all experience-based tasks. In every other professional category we have higher average values. For blue collar workers, we observe a strong focus on knowledge-based tasks, i.e. around 19 percent of knowledge-based tasks and only 7 percent of experience-based tasks. In contrast the difference between knowledge and experience-based tasks is rather small for white collar workers. This makes sense if one considers that blue collar workers probably participate directly in the production process and have less contact with clients. White collar workers, in contrast, can either perform technical jobs, like engineers or computer technicians, or highly client-related jobs in the service sector. The same reason could explain why civil servants perform a rather large share of experience-based tasks as these jobs are mostly less related to technology.

In the fifth and sixth columns we show the tasks distributions according to educational level. The results tell us that a larger amount of human capital in the form of educational level leads people to perform a larger set of different tasks. This holds for either knowledge or experience-based tasks as the shares are (at around 25 and 34 percent) highest for individuals with a university degree. Individuals holding neither an apprenticeship degree nor a university degree, in contrast, have the lowest values for both task categories.

The last two columns of Table 2.1 present the results of the task distribution according to worker gender. The first row tells us that females perform a bigger share of experience-based tasks, whereas the second row shows that males perform on average more knowledge-based tasks. This result is in line with the fact that in Germany, more men study technical subjects or hold jobs involving technical content.

2.5.2 Regression results for the first specification

To show how the composition of tasks affects workers' wages, we present the estimation of equation (2.5) according to our first measure in Table 2.2. Hence, in Table 2.2 we stayed with the task measure, which differs in every wave. We estimated eight specifications; two for each wave.

Thus, we have one specification where we regressed the logarithmic monthly wage on our main variables of interest without further controls (i.e., equation (2.5) without) and one specification with the full set of variables.

Table 2.2: Mincer type regression with logarithmic monthly wage as dependent variable (first specification)

	1979 I	II	1985/86 III	IV	1991/92 V	VI	1998/99 VII	VIII
Exp	0.030*** (28.00)	0.021*** (21.82)	0.032*** (30.13)	0.025*** (25.10)	0.029*** (24.38)	0.021*** (19.42)	0.023*** (14.66)	0.019*** (12.87)
Exp^2 $\times 100$	-0.059*** (29.04)	-0.043*** (24.00)	-0.062*** (29.67)	-0.052*** (27.53)	-0.049*** (22.62)	-0.038*** (19.94)	-0.031*** (13.13)	-0.029*** (13.87)
Kbt	0.042*** (21.73)	0.015*** (8.66)	0.018*** (27.04)	0.006*** (9.53)	0.018*** (26.42)	0.007*** (10.72)	0.010*** (20.60)	0.004*** (9.56)
$Kbt \times Exp$ $\times 100$	0.013 (1.25)	-0.002 (0.21)	-0.001*** (2.94)	0.004 (1.27)	-0.018*** (6.05)	-0.005** (2.19)	-0.009** (4.42)	-0.004** (2.53)
Ebt	0.007*** (3.78)	-0.004** (2.26)	0.011*** (18.58)	0.002*** (4.03)	0.012*** (18.31)	0.004*** (6.37)	0.005*** (13.56)	0.001*** (3.37)
$Ebt \times Exp$ $\times 100$	0.025** (2.52)	0.053*** (6.42)	0.016*** (5.49)	0.02*** (7.64)	0.008*** (2.96)	0.013*** (5.17)	0.001 (0.54)	0.005*** (3.51)
Contr.	No	yes	no	yes	No	yes	no	yes
Obs.	15278	15278	15330	15330	13808	13808	11871	11871
R^2	0.2	0.4	0.26	0.45	0.23	0.44	0.18	0.37

Note: All data are drawn from the BIBB/IAB Strukturerhebung 1979-1998/99
The dependent variable is the log monthly income.
Controls are sex, firm size, type of education and professional status.
Robust standard errors are used. t-values under coefficients.
* Denotes significant at 10 percent level.
** Denotes significant at 5 percent level.
*** Denotes significant at 1 percent level.

The coefficients of experience and experience squared show the typical signs and power. However, let us take a look at the main variables of interest. If we first consider the variables on the share of all possible knowledge-based tasks (*kbt*) and the share of all possible experience-based tasks (*ebt*), we find significant positive values throughout all specifications apart from specification II, where the variable of *ebt* is significant and negative. However, apart from specification II, the results indicate that whenever the share of tasks demanded by a certain job rises, the person earns a significantly higher wage and it is irrelevant whether the tasks are knowledge-based or experience-based. This outcome is reasonable from a human capital perspective. A higher demand of various tasks in a job should lead to a higher ability and therefore higher individual productivity.

More interestingly, the share of all possible knowledge-based tasks always gives us a bigger coefficient then the share of experience-based tasks. Thus, at the beginning of a career (with 0 years of experience), a one percent increase in the share of knowledge-based tasks always leads to a higher wage advantage than a one percent increase in the share of experience-based tasks. Now, considering the interaction term $Ebt \times Exp$ for knowledge-based tasks, we have either significant negative coefficients for specifications III and V to VIII or coefficients that do not differ from zero. This indicates that a given share of knowledge-based tasks will either not give individuals an extra wage advantage if they progress in their careers or can even harm them with respect to workers holding jobs with a lower share of knowledge-based tasks. With respect to the theory of Mincer (1974), specifications III and V to VIII confirm our theory that the rate of human capital depreciation is higher when the share of knowledge-based tasks is higher. The coefficients are significant and negative and therefore indicate an earlier peak holding everything else constant. Thus, the marginal rate of return for experience decreases at a faster rate if the share of knowledge-based tasks is high in a job.

However, in specifications I, II and IV, our theory is not confirmed by significant negative values.

Let us take a look at the interaction terms for $Kbt \times Exp$ for experience based tasks. All columns show significant positive effects. Hence, even if the wage advantage is somewhat higher for workers performing jobs with a high demand of knowledge-based tasks at the beginning of the career, performing jobs with a high demand of experience-based tasks seems to benefit mainly workers with longer careers. Thus, the earnings profiles peak later if the share of experience-based tasks is higher in a given job, assuming everything else to be constant. The marginal rate of return decreases slower for individuals performing higher shares of experience-based tasks in their jobs.

2.5.3 Regression results for the second specification

In Table 2.3 we present the results for our second specification measure of tasks. Here we present X specifications as we added two specifications of the pooled sample; one with controls and one without controls. Now, as explained above, we have the same measures for the task portfolios in every wave, and hence, results are more comparable. As in Table 2.2, the results in Table 2.3 support our theory. We also observe that the coefficients of Kbt and Ebt are positive and significant and the coefficient of kbt is always higher. Moreover, we observe a significant negative coefficient for $Kbt \times Exp$ and a positive one for $Ebt \times Exp$. Thus, as predicted by our theory, experience earnings profiles peak earlier if the share of knowledge-based tasks demanded by a job is higher given the share of experience-based tasks and vice versa. Moreover, the magnitudes of the coefficients seem to be quite stable and cannot be controlled away by the incorporation of further control variables. This indicates that we indeed measure a similar effect in every wave.

Table 2.3: Mincer type regression with logarithmic monthly wage as dependent variable (second specification)

	1979		1985/86		1991/92		1998/99		Pooled	
	I	II	III	IV	V	VI	VII	VIII	IX	X
Exp	0.034***	0.024***	0.032***	0.025***	0.027***	0.021***	0.023***	0.020***	0.029***	0.022***
	(28.81)	(23.04)	(31.84)	(26.82)	(23.78)	(19.95)	(17.24)	(16.21)	(53.42)	(43.92)
Exp^2	-0.06***	-0.045***	-0.062***	-0.052***	-0.047***	-0.038***	-0.031***	-0.03***	-0.051***	-0.041***
$\times 100$	(29.18)	(24.68)	(29.68)	(27.71)	(21.81)	(19.68)	(13.38)	(14.17)	(48.60)	(43.48)
Kbt	0.017***	0.006***	0.017***	0.006***	0.019***	0.008***	0.018***	0.009***	0.018***	0.007***
	(25.45)	(9.77)	(26.50)	(9.88)	(27.83)	(12.63)	(23.73)	(12.19)	(52.02)	(22.41)
$Kbt \times Exp$	-0.019***	-0.015***	-0.013***	-0.001	-0.019***	-0.01***	-0.018***	-0.011***	-0.016***	-0.008***
$\times 100$	(5.77)	(5.05)	(4.26)	(0.52)	(6.66)	(3.98)	(5.40)	(3.48)	(10.57)	(5.67)
Ebt	0.007***	0.001**	0.007***	0.001***	0.006***	0.002***	0.006***	0.002**	0.006***	0.002***
	(12.17)	(2.45)	(14.83)	(2.80)	(11.80)	(3.84)	(9.65)	(2.52)	(24.73)	(6.13)
$Ebt \times Exp$	0.007**	0.013***	0.012***	0.015***	0.013***	0.015***	0.004	0.008***	0.009***	0.012***
$\times 100$	(2.44)	(5.68)	(5.29)	(6.95)	(5.40)	(5.73)	(1.49)	(3.46)	(7.53)	(11.21)
Contr.	no	yes	no	yes	no	yes	no	yes	no	yes
Obs.	15278	15278	15330	15330	13808	13808	11871	11871	56287	56287
R^2	0.19	0.4	0.27	0.45	0.25	0.44	0.2	0.38	0.46	0.59

Note: All data are drawn from the BIBB/IAB Strukturerhebung 1979-1998/99
The dependent variable is the log monthly income.
Controls are sex, firm size, type of education, professional status and year dummies for IX and X.
Robust standard errors are used. t-values under coefficients.
* Denotes significant at 10 percent level.
** Denotes significant at 5 percent level.
*** Denotes significant at 1 percent level.

To illustrate the results of table 2.3 we plot the earnings profiles according to the estimation results in table 2.3 for three hypothetical task sets. The first task set puts a high weight on knowledge-based tasks and a low weight on experience-based tasks. The second task set puts a high weight on experience-based tasks and a low weight on knowledge based tasks and the third task set puts equal weights on both knowledge and experience-based tasks.

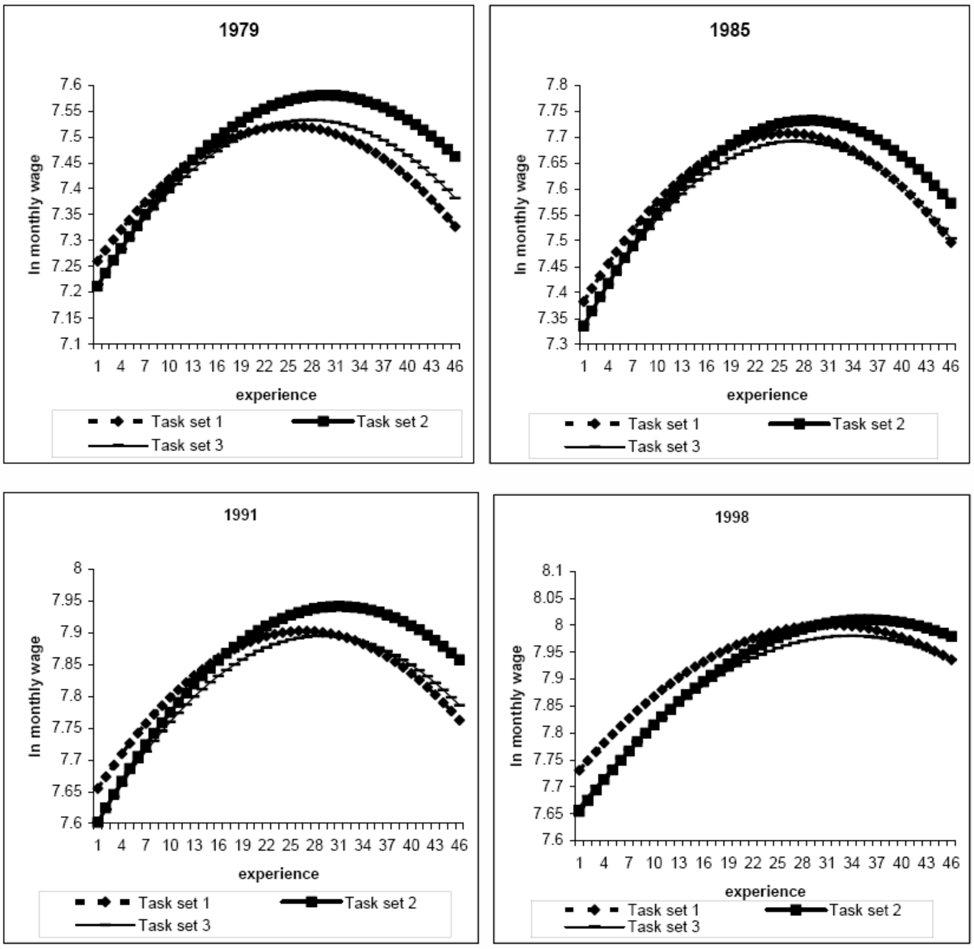

Figure 2.1: Experience earnings profiles by task set
Note: Task set 1: 75 percentile of kbt=22.863 and 25 percentile of ebt=7.896; Task set 2: 50 percentile of kbt=11.251 and ebt=25.414; Task set 3: 25 percentile of kbt=14.112 and 75 percentile of ebt=14.791

All plotted graphs stem from the extended regressions with further controls. The y-axis refers to the log monthly wages and the x-axis represents the amount of experience. We plotted the graphics for every year separately. We excluded the graphic for the pooled sample but the results are qualitative the same.

The graphics reveal that the rate of depreciation is higher for individuals performing a high share of knowledge-based tasks as the profiles of task set 1 peak the earliest in every cross section. For example, in 1979 the wage profile of the first task set peaks at around 24 years of experience whereas the wage profile of task set 2 peaks at around 28 years of experience. Hence, for task set 1 we can say that people with 24 years of experience earn more than for example individuals with 40 years of experience. In contrast we find the maximum of the wage profile for task set 2 four years later with 28 years of work experience. Thus, especially if workers focus on knowledge-based tasks they suffer from depreciation and earn less with respect to their younger colleagues.

Moreover, the graphics illustrate that younger workers (i.e. workers of recent vintages) even benefit over workers with other task combinations if they perform mainly knowledge-based tasks in their jobs. Thus, for the first years of experience the wage profiles of the first task sets exceed the profiles of the other task sets. However, later in the career the wage paths are exceeded by the wage profiles of task set 2 and task set 3. Especially, the profile of the latter set (i.e. set which has the focus on experience-based tasks) shows high wages at the end of careers. Thus, workers of older vintages benefit if they focus on experience-based tasks.

Appendix A

A.1 Tables

Table A.1: Descriptive statistics for all variables used in the investigation

Variable	Std. Dev.	Mean	Max	Min
Tasks:				
Knowledge based tasks (kbt)	7.701	16.604	37.821	3.643
Experiecne based tasks (ebt)	10.427	16.979	54.375	0
Ln(monthly wages)	0.448	7.936	9.159	6.551
Experience	11.921	18.24	45	0
Sex	0.462	0.309	1	0
Education:				
Low education	0.364	0.157	1	0
Medium education	0.436	0.744	1	0
High education	0.297	0.098	1	0
Frim size:				
Less then 5 employees	0.242	0.063	1	0
5-9 employees	0.319	0.115	1	0
10-49 employees	0.435	0.253	1	0
50-99 employees	0.324	0.119	1	0
100-499 employees	0.412	0.216	1	0
500-999 employees	0.256	0.071	1	0
More then 1000 employees	0.369	0.163	1	0

Note: All data are drawn from the BIBB/IAB Strukturerhebung 1979-1998/99.

Table A.2: Task categories for the BIBB/IAB Strukturerhebung from 1979

Experience based tasks	Knowledge based tasks
Advertising, PR-Work, Publicizing	Researching, analyzing, exploring
Buying, selling properties	Projecting, planning, making plans
Parenting, training, teaching; Consulting or counseling	Applying and using the law or rights
Negotiating, representing someoneŠs interests	Programming
Publishing, journalistically or literarily working	Repairing machines, equipment, vehicles and constructions
Organizing, planning, managing	Making constructions, sketching, modeling
Calling for customers, visiting firms or companies	Chemically-physically analyzing and examining
Renting, brokering objects	Medically-biologically analyzing and cytologically examining
Auctioning objects	Shorthanding, ciphering, coding
Serving, accommodating	Reporting, drawing up the balance sheet
Negotiating with customers or suppliers, advising customers	Making or interpreting statistics
	Evaluating data processing
	Working out laws or regulations
	Examining, appraising, estimating
	Using, equipping, and maintaining a computer, software, terminals and monitors

Note: All data are drawn from the BIBB/IAB Strukturerhebung 1979.

Table A.3: Task categories for the BIBB/IAB Strukturerhebung from 1985/86

Experience based tasks	Knowledge based tasks
Buying, advising, advertising	Researching, analyzing, measuring, examining
Parenting/teaching, training, consulting	Making constructions, sketching, designing
Publishing, entertaining, presenting	Applying and using the law or rights, registering
Managing, employing personnel	Programming
Organizing, planning, managing, leading	Equipping machines
Entertaining	Operating machines
Serving, accommodating	Maintaining machines

Note: All data are drawn from the BIBB/IAB Strukturerhebung 1985/86.

Table A.4: Task categories for the BIBB/IAB Strukturerhebung from 1991/92

Experience based tasks	Knowledge based tasks
Buying, selling and advertising	Researching, analyzing, measuring, examining
Teaching, parenting and training	Making constructions, sketching, designing
Publishing, entertaining, presenting and designing	Applying and using the law or rights, registering
Coordinating, organizing and planning	Programming
Managing, employing personnel	Equipping machines
Serving	Operating machines
	Maintaining machines

Note: All data are drawn from the BIBB/IAB Strukturerhebung 1991/92.

Table A.5: Task categories for the BIBB/IAB Strukturerhebung from 1998/99

Experience based tasks	Knowledge based tasks
Training and teaching	Collecting and processing information
Consulting and providing information	Developing and researching
Buying, selling	Repairing
Organizing	Guarding and maintaining machines
Negotiating	
Marketing	
Serving, accommodating	

Note: All data are drawn from the BIBB/IAB Strukturerhebung 1998/99.

Table A.6: Job categories

Job categories	
Culturist	Carpenter, roofer, scaffolder
Animal breeder, fishery professions	Road and civil engineer
Administrator, adviser in agriculture	Builder's laborer
Agricultural workers, animal	Building decorator
Horticulturist	Interior decorator, upholsterer
Forest and hunting professions	Cabinetmaker, model maker
Miners	Painter, varnisher and related occupations
Mineral, petroleum and petroleum gas production	Goods examiner, transport dressing
Mineral processing	Unskilled worker
Brick machining	Machinist and related occupations
Construction material manufacturer	Engineer
Ceramist	Chemist, physicist, mathematician
Gaffer	Technician
Chemical worker	Technical specialist
Synthetical fabricator	Goods merchants
Paper manufacturer, paper fabricator	Bank and insurance employee

Continued on next page...

... table A.6 continued

Job categories	
Pressman	Other service occupations and related occupations
Wood preparation, wood fabrication	Occupations for ground transport
Metal manufacturer, roller	Occupations for sea and air transport
Former, caster	Occupations for communication
Metal forming (non-machining)	Chief storekeeper, storekeeper, transport worker
Metal forming (machining)	Entrepreneur, promoter, auditor
Metal surface machining, quenching and tempering	Delegate, important administrative occupations
Metal binder	Accounting clerk, data processing specialist
Forger	Office clerks, office hand
Fitter	Security services
Locksmith	Jailer
Machanician	Registrar
Toolmaker	Publicist, interpreter, librarian
Metalworker and related occupations	Artist and related occupations
Electrician	Doctor, pharmacist
Assembling and metal occupations	Remaining occupations of health care
Spinning occupations	Social worker and related occupations
Textile manufacturer	Teacher
Textile fabricator	Humanities and social science occupations
Textile refiner	Pastor
Leather manufacturer, leather and fur fabricator	Personal hygiene
Backery, confectioner	Guest attendant
Meat and fish fabricator	Housekeeping occupations

Continued on next page...

... table A.6 continued

Job categories	
Food preparation	Cleaner
Beverage and stimulants manufacturer	Remaining nutrition occupations
Bricklayer, concrete worker	

Note: All data are drawn from the BIBB/IAB Strukturerhebung 1979-1998/99.

Chapter 3

Wage flexibility and displacement losses.

3.1 Introduction

This chapter investigates how workers that perform different sets of tasks—i.e. workers in different occupations—suffer from income losses due to unemployment or wage reductions under different forms of wage bargaining systems. With such an investigation we contribute to the recent literature that payed a great deal of attention to the consequences of worker displacement for individual labor market outcomes.

Using data from the U.S., numerous studies investigate income losses of displaced workers and find that displacement is associated with severe and long lasting earnings losses on the order of 10-25 per cent. More recently, studies provide estimates of displacement losses for other parts of the world and in particular for Europe. These studies find much smaller displacement losses on the order of 6-10 per cent. Moreover, the wage losses in Europe are mostly related to reductions in working hours and periods of non-employment. In fact, employment effects in

Europe appear to be larger, with a significant impact on the probability of leaving the labour force permanently.

Some researchers argue that those differences in estimated displacement losses are a reflection of the genuine differences in the labor markets between the U.S. and Europe (e.g. Hijzen et al.; 2010). One major potential source that causes displacement losses to be bigger in the U.S. than in Europe might be differences in the wage formation process of both continents. In particular, the centralization of the wage bargaining system differs substantially between the US and Europe. The U.S. has low union coverage rates and free bargaining systems, whereas in Europe many countries have high union coverage rates and centralized wage bargaining systems. Therefore, employers in the U.S. can easily adjust their wages according to the economic situation whereas European employers cannot. As a result, European employees might not suffer wage losses, as long as they are able to find a subsequent job directly after displacement. However, attributing differences in displacement losses exclusively to differences in the wage formation process would be myopic, as European labor markets differ in many more ways from U.S. labor markets. Moreover, former studies use data sources that are hardly comparable across countries and estimated differences in displacement losses may arise because researchers rely on very different methods and data sources (Couch and Placzek; 2010).

Therefore, this paper contributes to the literature in two different ways. First, this paper investigates displacement losses under different forms of wage bargaining systems within one country. Second, we investigate displacement losses for individuals that work in different occupations and perform different kinds of tasks.

For our purpose, we estimate income losses for Danish workers that were displaced at different points in time between 1980 and 2004—a period in which Denmark underwent a substantial decentralization of it’s wage bargaining system.

Such an approach has the advantage that we can rely on a common data source and can apply the same methods under different wage bargaining systems and comparable economic conditions such that other country specific influences stay rather stable.

In particular, this paper estimates displacement losses for young apprenticeship graduates departing from firms that went out of business between 1980 and 2004. We argue that such an investigation is ideal to draw further conclusion about the relation between the centralization of the wage formation process and the size of displacement losses. First, the Danish wage bargaining system was strongly decentralized between 1980 and 2004. Until 1987 wages were set on the sectorial level, whereas since 1993 most wages are bargained at the firm level. Second, the Danish labor market is very flexible because employment protection and firing costs are very low. Therefore, the labor market is comparable to labor markets within bigger economies such as the U.S. or Britain which improves the external validity of our results. Third, we estimate displacement losses for young apprenticeship graduates because the Danish apprenticeship system ensures that those workers are able to perform a well-defined set of up-to-date tasks required for a particular job or occupation. Therefore, we have reliable categorization of the individuals occupation and do not have to rely on broader and unreliable categorizations according to an individuals industry such as other studies do. Moreover, we are able to investigate a very homogenous groups of workers having labor market relevant skills and a minimum requirement of ability at different points in time. Displacement losses for such a homogenous group of workers are less likely to mirror pure ability differences between displaced and non-displaced workers. Fourth, we focus on young workers who have recently graduated from their training program and do not differ too much in their firm specific investments. Thus displacement losses are less likely to display differences in firm characteristics between displaced and non-displaced workers. Fifth, the Danish statistical office provides access to unusually big and high quality administrative data sets for the whole population over a period of more than 20 years allowing us to investigate displacement losses very precisely.

Our findings reveal that displacement losses increased substantially after the wage formation process has been decentralized in Denmark—particularly within the first two years after displacement. Under a more flexible wage bargaining system displacement losses are bigger either in boom periods or in recessions than under an inflexible wage bargaining system in comparable economic situations. In particular, we find the following: First, displacement losses within the first 4 years after displacement increased substantially between 1980 and 2004 and in particular after 1987— the year after which wage bargaining was more and more decentralized. Second, in the 1980s we find that most displacement losses are attributed to spells of non-employment, whereas displacement losses in later periods remain substantially even after controlling for spells of non-employment. Fourth, from the beginning of the 1990s displaced workers are much more likely to end up in the lower parts of their firms wage distribution than during the 1980s. However, we fail to find substantial differences in displacement losses for individuals that are trained for different types of occupations. One possible explanation for such a result lies in the nature of the Danish apprenticeship system which assures that workers are able to perform labor market relevant tasks that are easy to transfer across firms. Moreover, we look particularly on young worker that do not differ substantially in their amount of specific human capital.

Yet our results provide a plausible explanation of why displacement losses differ so much between the U.S. and European countries. Thus even if data sets, methods and varying economic periods might induce differences in the estimation of displacement losses, our results suggest that the flexibility in the wage formation process influences displacement losses substantially.

The remainder of this chapter is structured as follows: In chapter 4.2 we present previous empirical literature on displacement losses from the U.S. and Europe and discuss the differences among those studies with regard to the flexibility of the wage bargaining system. In chapter 4.3 we describe the wage bargaining and apprenticeship system in Denmark to introduce the institutional background for our investigation. Chapter 4.4 describes our estimation methods and chapter 4.5 the data and identification. Chapter 4.6 presents the results and chapter 4.7 concludes.

3.2 Empirical literature

This section describes and compares prior U.S. and European studies on displacement losses and explains the background of these studies in greater detail.

We begin with US—with it's flexible wage bargaining system—where researchers estimate usually big and long lasting displacement losses. We can distinguish two broad categories of empirical works on displacement losses. Studies of the first category use mostly survey based data. Farber (1993) and Farber (1997) use the Displaced Worker Survey and find displacement losses of around 9 to 12 per cent. Stevens (1997) and Ruhm (1991) use the Panel Study of Income Dynamics and find losses of around 14 to 30 per cent. Couch (1998) and Chan and Stevans (2004) find up to 50 per cent of income losses by using the Health and Retirement Survey.

The other category of studies uses large scale register based employer-employee data sets that are similar to the data we use. The most famous example among those studies is Jacobsen et al. (1993). Using data from Pennsylvania, Jacobsen et al. (1993) find displacement losses up to 40 per cent for long tenured workers who did not suffer from periods of unemployment during the entire observation period. Schoeni and Dardia (1997) find displacement losses of about 25 per cent. By showing genuine wages losses for the employed Schoeni and Dardia (1997) confirm the results of Jacobsen et al. (1993). However, Schoeni and Dardia (1997) show that most of the initial wage loss estimated for the whole population (not only the employed) stem from some form of unemployment spells. More recent studies, such as Hildreth et al. (2005), who use data from California find somewhat lower losses in the range of 12 to 16 per cent and Couch and Placzek (2010)—using data from Connecticut—find income losses up to 33 percent .

In contrast to the U.S. evidence, most European studies find displacement losses to be rather small or even non-existing. Couch (2001) uses data from the German Socio Economic Panel—a household-level longitudinal survey—and finds an earnings loss of about 13.5 per cent in the first year after displacement that declines towards 6 per cent in the second year after displacement. Burda and Mertens (2001) estimate displacement losses for the same German Socio Economic Panel in combination with a German register data panel (IAB) and confirm that income losses after displacement are very low. They even find income gains for lower percentiles of the income distribution. Bender et al. (1999), using the same IAB data source in comparison with a large register data set from France, find very small displacement losses for both countries. von Wachter and Bender (2006) use a German linked employer-employee data set and focus on young apprenticeship graduates for whom they find displacement losses of about 15 per cent that fade to zero within 5 years after displacement. Bender et al. (1999) argue that displacement losses in Germany and France are rather small and short lasting as both countries have strongly regulated labor markets in which wages are bargained between employers and labor unions for industrial sectors. Austria has a bargaining system similar to the German system and Ichino et al. (2007) find displacement losses for Austrian workers of about 5 per cent.

Eliason and Storrie (2006) estimate displacement losses for displaced workers using Swedish register data. Their sample consists of workers that were displaced in 1987 and the researchers follow those workers until 1999. They find displacement losses of about 6 per cent. In 1987 the Swedish wage bargaining system was highly centralized but like in Denmark the wage bargaining system was decentralized substantially after 1987.[1]

Using British data for the years between 1994-2003, Hijzen et al. (2010) find displacement losses up to 35 per cent. In Britain the wage bargaining system was strongly decentralized during the period between 1994 and 2003. Even if dis-

[1]For a detailed description of the bargaining system in Sweden, Denmark and Austria compare Iversen (1996).

placement losses are quite big compared to other European countries most of these losses are due to spells of unemployment such as in other European countries.

The previous evidence on displacement losses shows a variety of results that differ substantially depending on the data sets and methods. However, there is a tendency that displacement losses are bigger in the US than in most European countries. Even among European countries the evidence is not consistent. Previous estimates show, for example, that displacement losses are quite high in Britain but rather low in Germany. Yet the former evidence indicates a tendency that displacement losses are smaller in countries with rigid wage bargaining systems and bigger under more flexible wage bargaining systems. However, the applied methods and data sets are too different across countries such that it is difficult to draw a final conclusion. The next sub-section presents the institutional framework in Denmark and explains how we make use of this particular setting to investigate how displacement losses evolve under different forms of wage bargaining systems.

3.3 Institutional background

The Danish labor market is characterized by considerable job mobility and an extensive social safety net for the unemployed. Between 25 and 35 per cent of the workforce changes employers each year. These job changes involve periods of unemployment because between a third and a quarter of the labor force is affected by shorter unemployment spells in any given year. Firing costs are limited compared to those in other European countries. Thus the low level of employment protection is more similar to that found in Britain or the US (Albæk and Sørensen (1998)). As the objective of this paper is to investigate displacement losses under different types of wage bargaining systems, we describe the nature and changes in the Danish bargaining system in the first subsection of this chapter. The second subsection describes the Danish apprenticeship system and argues why Danish apprentices are the ideal group of individuals to study displacement losses at different points in time.

3.3.1 The Danish wage bargaining system

The Danish labor market between 1980 and 2004 provides us with the ideal setting to investigate how the flexibility in the wage formation process affects long term displacement losses.

In general, the Danish labor market is well organized with more than 70 percent of the work force organized in trade unions. However, although the Danish wage bargaining system has traditionally been fairly centralized, the 1990s are characterized by a shift to a more and more decentralized wage bargaining system. In the beginning of the 1980's wages were set in biannual national wage negotiations. General wage negotiations took place between the Danish Federation of Trade Unions and the Danish Employer Federation. Although only about

40 per cent of the private sector labor force was employed in firms where both the employees and the employer were organized, the great majority of employers and most workplaces applied the results of the general agreement.

From the beginning of the 1980s, there has been a tendency to a more decentralized of wage bargaining system. A first step was the abolishment of the wage indexation in 1982. From 1987 to 1993 negotiations concerning wages were done at the industry level. Although wage bargaining was still restricted and coordinated within strict guidelines, already in 1993 71 per cent of all agreements in the manual labor market were negotiated at the firm level. The guidelines were finally abandoned in 1993 (Aagaard et al.; 2004). As shown by Iversen (1996), Denmark underwent a sharp drop in wage centralization during 1987 and 1993. The change from a centralized to decentralized wage bargaining system was faster and stronger in Denmark than in most other nordic countries.

3.3.2 The Danish apprenticeship system

We estimate displacement losses of young Danish apprenticeship graduates because the Danish apprenticeship systems ensures that those individuals are particularly homogeneous with respect to their labor market relevant skills and abilities. Focusing on such a homogeneous group has the advantage that we do not estimate displacement losses that are mostly attributed to ability differences or differences in firm characteristics between displaced and non-displaced workers. Moreover, as the apprenticeship system is steadily reformed to meet the requirements of the labor market, we minimize the likelihood that displacement losses mirror macro economic shocks affecting particular sub-groups of workers with out-dated skills. Therefore, our approach ensures the comparability of the results over the years in the most possible way.

We provide a short overview of the Danish apprenticeship system. For a more detailed description, see Wiborg and Cort (2010). Between 30 and 40 percent of a cohort enters basic vocational education. As in states like Germany or Switzerland, the Danish apprenticeship system is a "dual system" in which apprentices receive formal schooling and training on the job. The first company training period follows a one-year period of school-based training. During the company training itself, individuals also receive school-based training through approximately six school-based training periods lasting around 10 weeks each. Apprenticeship training can take up to 5.5 years, and most apprenticeships range from 3.5 to 4.5 years. Companies pay their apprentices during the training and the schooling period. During the schooling period employers are reimbursed via the employers' reimbursement fund, which is financed by a levy from all employers. Upon graduation of the apprenticeship training program, a vocational student acquires a qualification that corresponds directly to a specific occupational profile in the labor market.

Social partners are actively working to ensure the quality and to specify the requirements of each training program. The National Advisory Council for Initial Vocational Education and Training and the local training committees advise colleges on local educational plans and other local training matters to ensure that training requirements are fulfilled and apprenticeship graduates are equipped with up-to-date skills. Vocational training is based on broad occupational profiles that ensure that students acquire skills that are similar within each occupation and are transferable between companies. Thus vocational training facilitates the labor market mobility (Wiborg and Cort; 2010).

3.4 Methods

The following chapter discusses general problems of estimating displacement losses discussed in the literature, and presents our empirical methods to overcome those problems. To explain our regression approach we rely on a simple model from von Wachter and Bender (2006).

Assume that young workers wages or income are a function of their innate skills a_i and their mobility status. Thus let D_{i0} be a dummy variable indicating whether an individual left his or her training firm. Leavers include voluntary movers who benefit from mobility and involuntary movers who are likely to be low quality apprentices who leave their training firms because their employers did not offer them a subsequent contract. Thus we have $D_{i0} = V_{i0} + I_{i0}$ where $V_{i0} = 1$ if the movement is voluntary and $I_{i0} = 1$ if the movement is involuntary. The gain of voluntary movement is δ_{Vt} and the displacement loss is δ_{It}. The goal of our study is obtaining an estimate for the displacement loss δ_{It}. Usually we are not able to observe V_{i0} and I_{i0} separately. Therefore, we follow the evaluation literature and identify a treatment group of involuntary movers and compare those movers to a control group of stayers that are otherwise identical to our treatment group.

To identify a proper treatment group of involuntary movers the problem of firm internal sorting of leavers is not the only problem which arises. The second problem is the initial sorting of workers across firms. Displaced workers are disproportionaly selected from firms with higher turnover rates which might attract less able apprentices. As a result the average ability of workers from a leavers firm might be lower than the average ability of workers of a stayers firm—as a consequence our treatment and control group would not be identical. Thus let $\bar{a}_{j(i)}$ be the average ability of workers in firm j. Finally, we can write the income generating process as

$$Y_{it} = \delta_{It} D_{i0} + (\delta_{Vt} - \delta_{It}) V_{i0} + (a_i - \bar{a}_{j(i)}) + \bar{a}_{j(i)} + \varepsilon_i \tag{3.1}$$

where ε_i is a random disturbance term. Thus income is determined by the mobility status, an individual's component relative to the average training firm $(a_i - \bar{a}_{j(i)})$ and a firm specific component $\bar{a}_{j(i)}$. In general neither $(a_i - \bar{a}_{j(i)})$ nor $\bar{a}_{j(i)}$ are observable by the econometricians and a simple OLS estimate of δ_{Vt} after t years would yield to:

$$plim \hat{\delta}_{It}^{OLS} = \delta_{It} + (\delta_{Vt} - \delta_{It}) \frac{Cov(V_{i0}, D_{i0})}{Var(D_{i0})} + \frac{Cov(a_i - \bar{a}_{j(i)}, D_{i0})}{Var(D_{i0})} + \frac{Cov(\bar{a}_{j(i), D_{i0}})}{Var(D_{i0})} \tag{3.2}$$

Equation (3.2) shows three potential sources of bias. The second term on the right hand side of equation (3.2) displays a bias which arises because of the firm internal selection problem of movers and stayers. The third term displays the bias which arises because of an individual specific error term which is not related to the average firm specific error. The fourth term on the right hand side displays the error which arises because of a training firm specific error. We underestimate the displacement effect if voluntary movement is predominant ($(\delta_{Vt} - \delta_{It}) \frac{Cov(V_{i0}, D_{i0})}{Var(D_{i0})} Y > 0$). In contrast we overestimate the displacement effect if less able workers are likely to change their establishments more often ($\frac{Cov(a_i - \bar{a}_{j(i)}, D_{i0})}{Var(D_{i0})} < 0$) and if less able workers are sorted into firms with high turnover ($\frac{Cov(\bar{a}_{j(i), D_{i0}})}{Var(D_{i0})} < 0$).

Thus we have to assure that we distinguish involuntary movers who suffer a real displacement from those who move voluntary from the firm. We rely on an approach which is widely recognized in the literature of displaced workers and create a sample of displaced workers leaving closing firms (e.g., Eliason and Storrie; 2006; Hijzen et al.; 2010). In order to investigate a very homogeneous group of workers, we restrict our sample to workers in firms that close down in a short time-window after the workers' apprenticeship graduation—i.e. the firm closure has to occur within the first three years after the graduation. Focusing exclusively on displacement due to establishment closure diminishes the selection problems because all workers are displaced regardless of their individual characteristics and behavior. If firm closure is a proper treatment, we are able to remove the bias which is displayed in the second term of equation (3.2).

However, unobserved individual heterogeneity and initial sorting of movers and stayers across firms still bias the estimates of the displacement effect δ_{It}. Under the assumption that income reflects the workers skills, and the selection into the treatment and control group or in the closing and non-closing firms is on the basis of an unobserved permanent income component, we are able to remove the bias displayed by the third and fourth term of equation (3.2) by applying the following regression:

$$Y_{it} = \alpha_i + \gamma_t + X_{it}'\beta + D_{it}^k \delta_k + \varepsilon_i \tag{3.3}$$

Equation (3.3) has become the "gold" standard in the literature on displaced workers. Y_{it} is individual i's annual earnings in year t, α_i is an individual-level fixed effect, γ_t is a vector of time effects, X_{it} includes time-varying individual characteristics. As most available variables such as experience, tenure or industry might be endogenous to the displacement, and therefore a form of displacement costs themselves, we limit our control variables X_{it} to age a squared term of age and a dummy for sex. D_{it}^k is a vector of dummy variables indicating each year after and during the individual's displacement. k indicates the year since displacement. In the following section we describe the data and will show exactly how we construct our control group of stayers and identify our treatment group of involuntary movers.

3.5 Data and identification

In this section we will describe the data in detail. First, we will give some general information and will describe how we select our sample and identify our treatment and control groups. In the second part of this section we describe the variables that we use for our investigation.

The 'Integrated Database for Labor Market Research' (IDA) covers each single individual and each single plant in Denmark from 1980 till 2004. The data is based on administrative records collected by the Danish Bureau of Statistics. There is no attrition with respect to individuals in IDA. The Danish Bureau of Statistics keeps track of every single Danish resident and assigns him or her to one and only one labor market state and plant in each year at a specific day in November. The data provides detailed information on labor market performance, such as earnings and experience, and a wide range of background characteristics such as educational background and family characteristics (Iversen et al.; 2006).

3.5.1 Sample design

For our investigation sample we select different cohorts of individuals which graduated from their apprenticeship training in different years between 1980 and 2004. As common in the literature estimating displacement losses for large register based data sets, we select a treatment group of displaced workers and a control group of workers not suffering displacement for every graduation cohort. In particular, we define a worker as displaced if he or she leaves a training firm that is out of business in the subsequent year. We follow Frederiksen and Westergaard-Nielsen (2007) and use a variable in the IDA that indicates whether firms went out of business. A problem present in all register based employer-employee data sources is to identify a firm closure whenever establishments change their formal identification number but remain in business. Statistics Denmark has corrected changes in the identity number for cases where it was obvious to Statistics Denmark that the firm remained in business. The main indicator used for the correction is the fraction of the workforce remaining employed. These corrections affect less than five percent of all firms.

Our treatment group of displaced workers consists of apprentices who left their training firm due to a firm closure within the first three years after their apprenticeship graduation. Our control group consist of apprentices from the same cohorts who graduated in firms which did not close down in the subsequent years. The control group includes employees who stay with their training firm for at least three years after their graduation. After those three years, we allow members of the control group to change their firms or become unemployed. Some other studies which mostly observe shorter periods of time create their counterfactual by considering only workers who stay in their firm for the whole observation period. As we are able to follow our individuals over a period of more than 18 years such an approach would not be appropriate. In particular, as the Danish labor market is very flexible and workers move between jobs even more than in the U.S.. Almost two thirds of the population suffer spells of unemployment during their work live and the average tenure is around 5.49 years for men and 5.45 years for women (Bingley and Westergaard-Nielsen; 2003). Therefore, a control group of stayers that remain in their training company for the whole observation period would not be representative in our case—particularly, as young workers are even more likely to move than older workers. As consequence we would end up with very few observations for the control group by relying on the approach of former studies.

We select cohorts of apprenticeship graduates from 1983, 1984 1988, 1989, 1992, and 1999 entering the labor market under different bargaining systems and economic conditions. The first two cohorts graduated in 1983 and 1984 were displaced between 1984 and 1987. We selected those two cohorts because we are able to obtain enough relevant information for each cohort before the displacement took place and we could assure that all workers of the treatment group were displaced under the rigid wage bargaining system that was persistent up to 1987. The treatment group of the cohorts from 1988 and 1989 were displaced between 1989 and 1992 during a period with a much more decentralized wage bargaining system. The cohorts of 1994 were displaced until 1997 and the cohort of 1999 were displaced until 2002—a point in time were all wages were already negotiated at the firm level.

For all graduation cohorts we select apprentices who are younger than 25 years at the end of their training period and spent at least two years in their training firm during their apprenticeship training. Gender-specific differences in the labor market attachment and income are very small in Denmark, such that we decided to keep male and female workers for our investigation. We dropped observations of individuals which left the country and self employed individuals. We stayed only with those individuals which are observable for at least 5 subsequent years after their graduation. These restrictions assure that we have a particularly homogeneous sample of workers with similar labor market relevant skills at different points in time.

3.5.2 Variables

Our variables contain individual and firm characteristics. Descriptive statistics on all variables are in the appendix. We use two different independent variables for the estimation according to equation (3.3). The first is the deflated annual sum of all yearly labor market earnings from all labor market activities. The base year for our deflation is 2000 and the variable is measured at some day in November. The yearly income represents a measure of the entire monetary endowment generated from working. Therefore, the yearly income includes all wages and income from different jobs. A displacement loss measured in the category of the entire yearly income represents the whole monetary loss and considers that individuals might work in different kinds of small jobs that are not registered as their main employment.

The other dependent variable measures the deflated hourly wages of the individual's main employer. Therefore, we can directly infer the displacement effect on the employers wage setting process. For both variables we allow spells of zero earnings, as spells of non-employment are a mayor consequence of a job loss. Restricting our sample to individuals who never suffer from non-employment after loosing their jobs would not be adequate as those individuals are a particular—high ability—group of workers who manage to find a subsequent job directly. However, we will precisely investigate which part of the income losses is related to unemployment and which part is related to wage reductions.

The independent variables in X_{it} are restricted to age, a squared age term and a dummy for gender. Moreover, we incorporate year dummies for every observation year. Like already mentioned we keep the control variables very sparse as most variables which we are able to use as control variables are endogenous to the displacement, and attribute to the displacement loss itself. Yet in some specification we include the amount of yearly working days as additional control to infer which part of the displacement loss is due to unemployment spells and which part refers to a reduction in wages.

3.6 Results

This section presents our estimation results. In Table 3.1 to 3.7 we present the results for the coefficient estimates of δ_{It} from equation 3.1 for each cohort of apprenticeship graduates. The first rows present the estimates for the first year after displacement by cohort year, the second rows presents the estimates for the second year after displacement and so forth. We present the estimates for the first 4 years after displacement as these years are observable for all cohorts. Yet we performed all regressions for the entire observation period but the differences are most significant during the first four years after displacement. In Figure 3.1 to 3.7 we plot the estimates of δ_{It} to illustrate the results graphically.

3.6.1 OLS results

Table 3.1 and Figure 3.1 show the raw OLS estimates. The dependent variable is the deflated yearly income of all working activities up to certain date in November. The only controls that we incorporate are year dummies to capture the general economic trend, sex, age and a squared term of age.

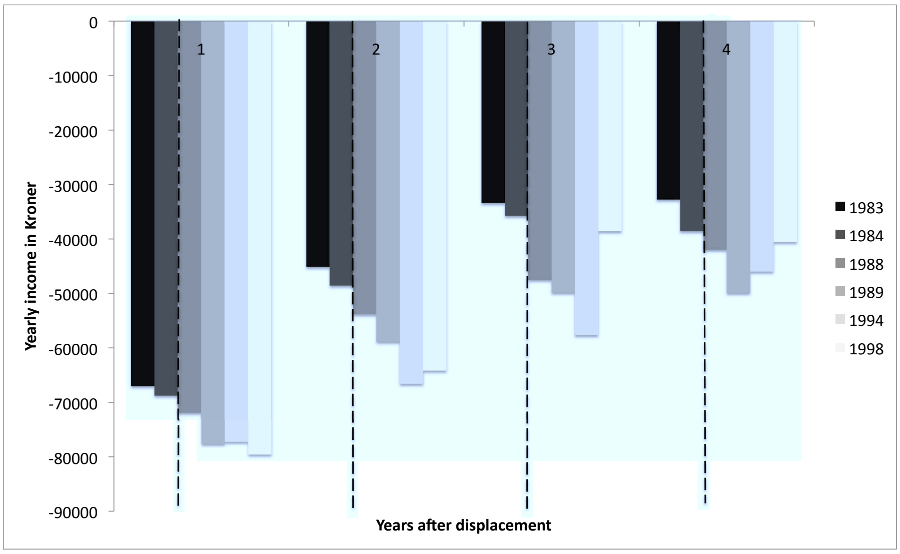

Figure 3.1: OLS results
Note: The bars represent the absolute amount of displacement losses. The dashed line represents the introduction of the flexible wage bargaining system.

The result show that displacement losses are substantial and significant even 4 years after displacement. Moreover, the losses rise substantially for each cohort since 1983. The raw displacement loss for the cohort of 1983 is about 67000 Kroner (12000 Dollar) of the real yearly November income and increases to about 79000 Kroner (14000 Dollar) for the cohort of apprenticeship graduates from 1999. Thus for the cohort of 1999 income losses in the first year after displacement are by about 10000 Kroners bigger than for the cohort of 1983. Displacement losses start rising for the cohort of 1988. This break is coincident with the time the wage bargaining system was decentralized substantially. This tendency is even more evident in the second year after displacement. Both rows show that displacement losses start growing from the 1988 cohort onwards. For the third and the fourth year after displacement, the displacement losses grow after 1988 but decline again for the cohort of 1999.

Table 3.1: Displacement losses: OLS estimates

	Years after displacement: 1	2	3	4
1983 cohort:	-67015.21 ***	-45123.81 ***	-33389.12 ***	-32761.95 ***
1984 cohort:	-68756.07 ***	-48552.51 ***	-35734.65 ***	-38539.56 ***
1988 cohort:	-71889.52 ***	-53810.87 ***	-47489.02 ***	-41959.55 ***
1989 cohort:	-77620.47 ***	-58846.54 ***	-49828.40 ***	-49894.34 ***
1994 cohort:	-77240.39 ***	-66589.11 ***	-57646.57 ***	-45981.06 ***
1999 cohort:	-79524.30 ***	-64174.08 ***	-38568.81 ***	-40559.87 ***

Note: All data are drawn from the IDA 1980-2004
* Denotes significant at 10 percent level.
** Denotes significant at 5 percent level.
*** Denotes significant at 1 percent level.

3.6.2 Fixed effect results

Up to this point we did not consider that workers might differ in their unobserved ability or training firm characteristics. Therefore, we include worker fixed effects in the next specification. Table 3.2 and Figure 3.2 show the results.

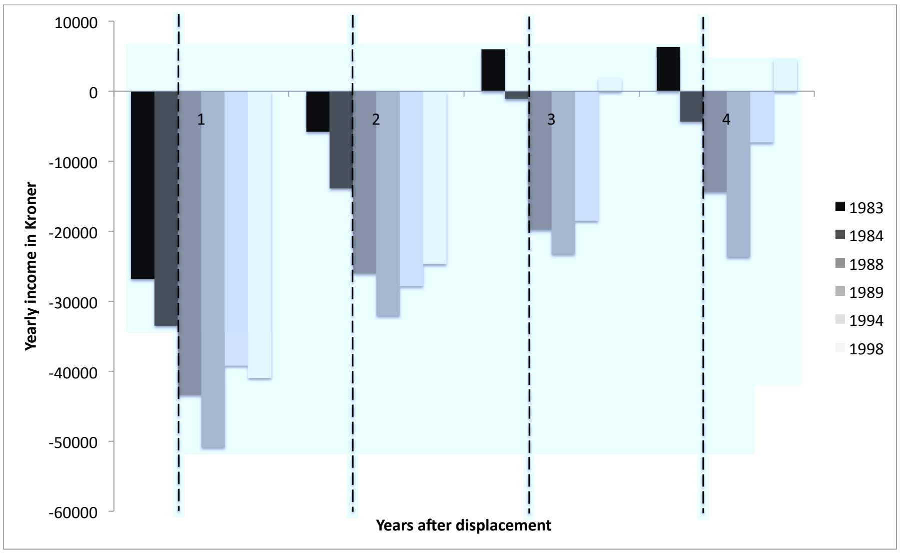

Figure 3.2: Fixed effects results I
Note: The bars represent the absolute amount of displacement losses. The dashed line represents the introduction of the flexible wage bargaining system.

Including worker fixed effects reduces displacement losses by half. In the first year after displacement earnings losses drop from 67000 to about 27000 Kroners for the cohort of 1983. In the cohort of 1999 the displacement loss decreases from about 79000 Kroners to about 41000 Kroners. Yet we observe that displacement losses rise substantially for the first and the second year after displacement. Therefore, the results of Table 3.2 and Figure 3.2 are qualitatively similar to those of Table 3.1 and Figure 3.1.

The rising trend in displacement losses is not as evident in the fourth year after displacement. In the fourth year after displacement, the negative effects remain only significant for the cohort of 1988 and 1989. For the cohort of 1983 the effect is even slightly positive significant now. This effect is rather surprising and it is hard to explain why it occurs only for the 1983 cohort. However, the effect is very small and only weakly significant.

Table 3.2: Displacement losses: Fixed effect I

	Years after displacement: 1	2	3	4
1983 cohort:	-26789.74 ***	- 5776.15 *	6017.2 *	6329.95 **
1984 cohort:	-33437.09 ***	-13855.69 ***	-1091.67	-4338.03
1988 cohort:	-43441.85 ***	-25968.44 ***	-19736.63 ***	-14329.64 ***
1989 cohort:	-50852.09 ***	-31985.49 ***	-23213.63 ***	-23615.14 ***
1994 cohort:	-39209.26 ***	-27798.44 ***	-18469.25 ***	-7289.68
1999 cohort:	-40964.7 ***	-24634.47 ***	1912.23	4536.50

Note: All data are drawn from the IDA 1980-2004
* Denotes significant at 10 percent level.
** Denotes significant at 5 percent level.
*** Denotes significant at 1 percent level.

As found by Eliason and Storrie (2006) displacement losses vary to a great deal according to the economic conditions under which individuals are displaced. Therefore, increasing displacement losses might be a pure reflection of economic cycles. Indeed, after the crisis in the early 1980s—in which unemployment rose to about 10 percent—a short period of recovery followed between 1984 and 1987. This period of recovery might be a possible reason that displacement losses for the cohorts of 1983 and 1984 are smaller than for the cohorts of 1988 and 1989. Unemployment rose to about 12 percent between 1988 and 1993. Yet the recovery period between 1984 and 1987 was rather short and unemployment remained on a high level of about 7.5 per cent. Moreover, displacement losses are still bigger for the cohorts after 1994. The years after 1994 where accompanied by a substantial economic boom, reducing unemployment to about 5 per cent within 5 years. Moreover, the youth unemployment for individuals under 25—i.e. our population of interest— was with 10.6 per cent substantially larger until 1985 than in all periods that followed.

We do not argue that displacement losses in Denmark are independent of macro economic conditions but our results indicate that the increase in displacement losses under the more flexible wage bargaining system are not pure results of a change in macro economic conditions.

3.6.3 Explorative results

This next subsection aims at investigating the results of the previous section in more detail. Specifically we aim at investigating the reasons for the patterns of the displacement losses. Up to this point the we only included explanatory variables that are strictly exogenous to the event of displacement. In this subsection we will add working days to the set of explanatory variables.Working days are not exogenous to the event of displacement but we still include this variable in the set of explanatory variables to investigate how our results change because of the inclusion of working days. Furthermore, we will replace our dependent variable of yearly income by two other variables. First we will perform our regressions with hourly wages as independent variable to show how the single employers wage setting evolves after a worker's displacement. Second, we will create dummy variables indicating the workers position in the firms wage distribution to infer in which hierarchical position of the post-displacement firm the displaced workers end up. Finally we will investigate the displacement losses of workers with different types of apprenticeship trainings.

Unemployment spells

In contrast to the U.S. in European countries displacement losses are mostly attributed to spells of non-employment and differences in the labor market attachment. Fortunately, our data contains detailed information about how many days a worker was employed at any given year. Thus to investigate whether displacement losses are mostly attributed to spells of non-employment, we include the total amount of yearly working days as additional control in the next specification. In this way we control for the fact that displaced workers might have a lower labor force attachment than non-displaced workers. Table 3.3 and Figure 3.3 present the results—as before worker fixed effects are included.

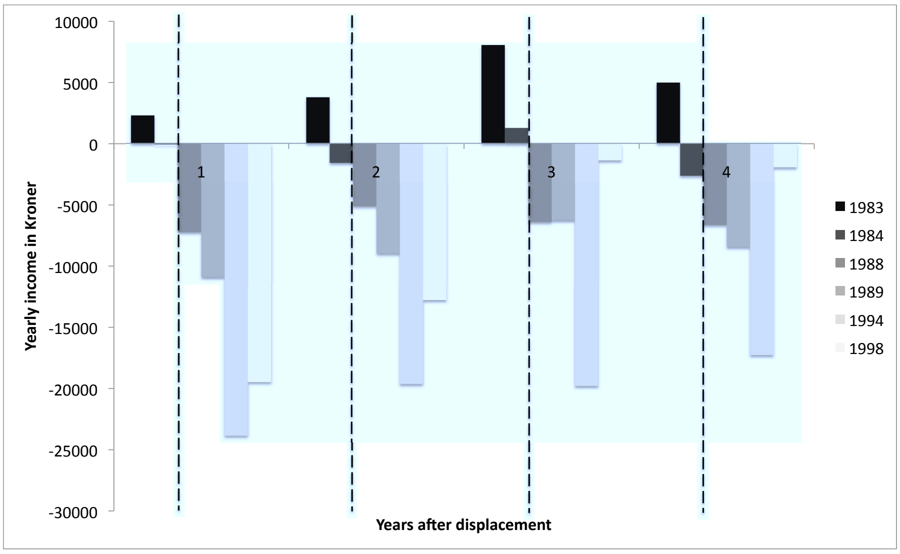

Figure 3.3: Fixed effects results II
Note: The bars represent the absolute amount of displacement losses. The dashed line represents the introduction of the flexible wage bargaining system.

If we control for differences in work days our results display displacement losses for workers having the same work experience. Thus under the assumption that unobserved ability is constant over our investigation period, the remaining displacement loss describes the wage penalty that a worker has to accept as consequence of displacement — even if the respective worker is constantly employed after his or her job loss. In contrast to the former results there are no significant displacement losses for the cohorts of 1983 and 1984 within the first four years after displacement. Some effects are even slightly positive significant. All displacement losses can be attributed to spells of unemployment for the cohorts of apprenticeship graduates being displaced during the rigid wage bargaining regime before 1987. This result is in line with former evidence from Europe.

In contrast the results look different for the cohorts between 1988 and 1999. Even after controlling for differences in the labor market attachment, we find remaining displacement losses which are in the order of about 7000 and 23000 Kroners for the first year after displacement and -2000 and -18000 Kroners for the forth year after displacement. In other words, after 1987 even displaced workers that remain constantly employed—i.e. find a job directly after being displaced—suffer income losses. This result indicates that under a flexible wage bargaining system employers can adjust the income for displaced workers and pay them a lower amount than their non-displaced counterparts. Such a picture is more closely to the evidence that was found in the US where displacement losses remain substantially even for the employed.

Table 3.3: Displacement losses: Fixed effect II

	Years after displacement:			
	1	2	3	4
1983 cohort:	2311.25	3786.62	8030.2***	4977.27**
1984 cohort:	-83.75	-1559.74	1292.76	-2590.13
1988 cohort:	-7214.54***	-5093.14***	-6386.73***	-6623.43***
1989 cohort:	-10884.27***	-8945.69***	-6239.43**	-8416.31***
1994 cohort:	-23856.68***	-19635.39***	-19795.58***	-17275.34***
1999 cohort:	-19481.82***	-12786.7***	-1357.26	-1911.48

Note: All data are drawn from the IDA 1980-2004
* Denotes significant at 10 percent level.
** Denotes significant at 5 percent level.
*** Denotes significant at 1 percent level.

Hourly wages

Even if income losses remain after controlling for differences in the labor market attachment, those income losses might stem from a reduction in working hours for displaced workers and might not be attributed to a wage reduction imposed by the employer. Therefore, the next specification replaces the dependent variable of the total yearly income from all work activities by the hourly wage at the main employer. Table 3.4 and Figure 3.4 display the results.

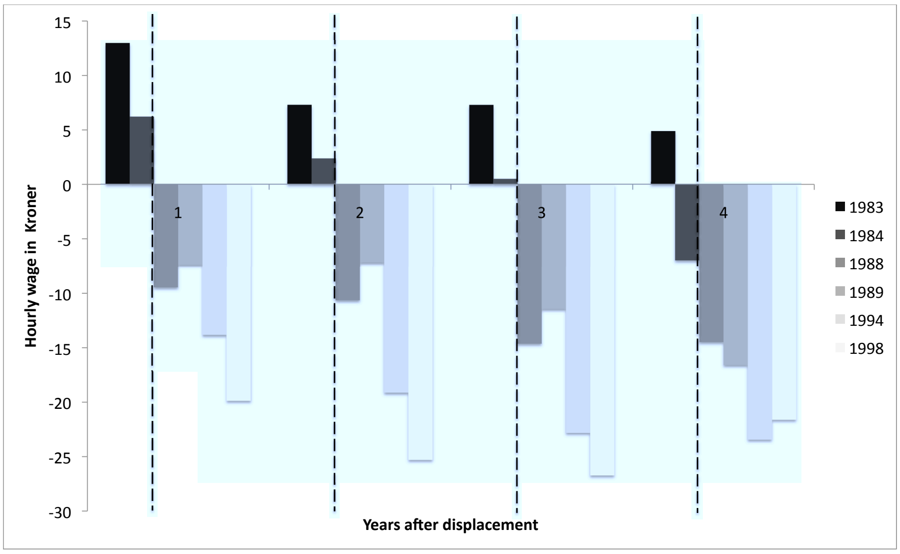

Figure 3.4: Hourly wages
Note: The bars represent the absolute amount of displacement losses. The dashed line represents the introduction of the flexible wage bargaining system.

The evidence shows that displacement losses are either slightly positive significant or not significant different from zero for the cohorts of 1983 and 1984. However, for the cohorts of apprenticeship graduates being displaced in periods with a very flexible wage bargaining system, displacement losses are substantial and increase considerably. Moreover, displacement losses in hourly wages do not decline within the first four periods after displacement but rather increase somewhat in later periods. The rise in wage loss is in line with former evidence from Sweden (Eliason and Storrie; 2006).

Table 3.4: Displacement losses: Hourly wages

	Years after displacement:			
	1	2	3	4
1983 cohort:	12.97 ***	7.31***	7.3***	4.91**
1984 cohort:	6.23**	2.4	0.54	-6.95***
1988 cohort:	-9.46***	-10.64***	-14.61***	-14.47***
1989 cohort:	-7.35**	-7.14**	-11.43***	-16.57***
1994 cohort:	-13.8***	-19.13***	-22.8***	-23.43***
1999 cohort:	-19.88***	-25.27***	-26.69***	-21.61***

Note: All data are drawn from the IDA 1980-2004
* Denotes significant at 10 percent level.
** Denotes significant at 5 percent level.
*** Denotes significant at 1 percent level.

Firms income distribution

If the wage bargaining system is very rigid because wages are fixed according to certain standards such as education, age and tenure, workers with similar work experience and comparable educational degrees should receive rather similar wages. Thus they should end up in similar parts of the wage distribution within the respective firm—in particular if the workers are young and do not differ systematically in their unobserved characteristics and their tenure. The employer has less possibilities to pay new hires lower wages or pay internal workers firm specific bonuses. Therefore, we should expect that young displaced apprenticeship graduates end up in similar position of their new firms wage distribution than those apprenticeship graduates that remained in their training firm if the wage bargaining system is rigid.

To test this expectation, we use information for every worker within each single firm to calculate the median of each firms income distribution. Afterwards we create a dummy which is 1 whenever the worker receives an income that is above the median income in the respective firm and zero otherwise. Such indicator displays whether workers end up in rather different parts of their entire firms income distribution. Moreover, such an approach takes into account that displaced workers might end up in firms that pay lower wages in general. We use this variable as dependent variable in a linear probability model including, year dummies, gender, age and yearly working days as explanatory variables. Moreover, we include worker fixed effects. Table 3.5 and Figure 3.5 display the results of this approach.

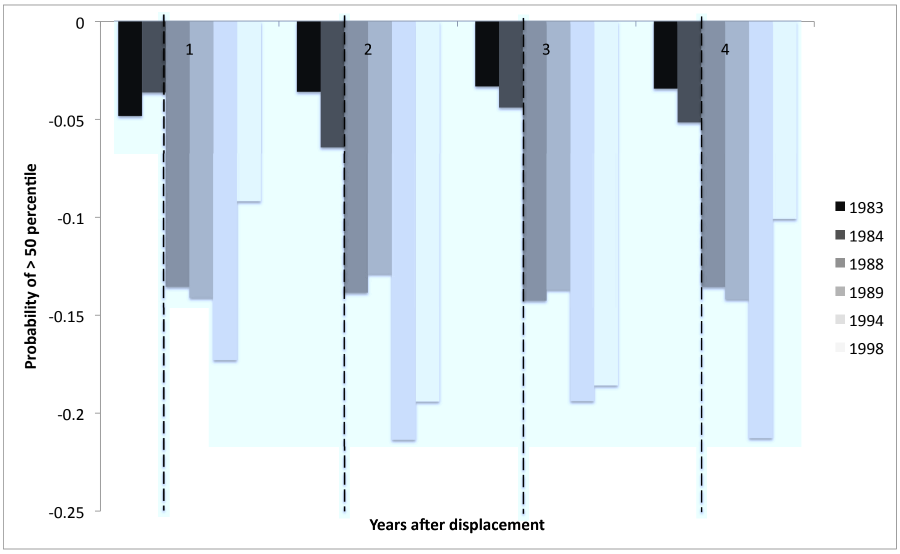

Figure 3.5: Income distribution
Note: The bars represent the absolute amount of displacement losses. The dashed line represents the introduction of the flexible wage bargaining system.

The table shows slightly negative but significant effects for the cohorts of 1983 and 1984 indicating that displaced workers are slightly less likely to end up in the upper tail of their firms wage distribution than their non-displaced counterparts. In contrast, the effect for the later cohorts for whom the wages are much more flexible are far bigger. Displaced workers are far less likely to end up in the upper tail of their firms income distribution than their non-displaced counterparts. Thus in times of a more flexible bargaining system, displaced workers are more likely to end up in lower parts of their firms income distribution.

Table 3.5: Displacement losses: 50 percentile

	Years after displacement:			
	1	2	3	4
1983 cohort:	-0.048***	-0.036***	-0.033***	-0.034***
1984 cohort:	-0.036***	-0.064***	-0.044***	-0.052***
1988 cohort:	-0.135***	-0.138***	-0.142***	-0.135***
1989 cohort:	-0.141***	-0.129***	-0.137***	-0.142***
1994 cohort:	-0.173***	-0.214***	-0.194***	-0.213***
1999 cohort:	-0.092***	-0.194***	-0.186***	-0.101***

Note: All data are drawn from the IDA 1980-2004
* Denotes significant at 10 percent level.
** Denotes significant at 5 percent level.
*** Denotes significant at 1 percent level.

Worker heterogeneity

Thus far we only considered the group of apprenticeship graduates as a whole. However, even if the group of apprenticeship graduates is very homogenous in comparison to the whole workforce, there are many different apprenticeship programs that lead to very different qualifications and might differ substantially with respect to their amount of firm specific human capital. Some apprenticeship programs might lead to skills that are easily transferable across jobs, firms and industries whereas other skills are not.

To create an even more homogenous sub-sample of workers this section looks on different groups of apprenticeship graduates separately. In particular, we focus on commercial apprenticeship graduates and apprenticeship graduates from the manufacturing sector. First, commercial and manufacturing workers represent the biggest apprenticeship programs where most people undertake their training. Second, both groups are usually considered to differ substantially in their human capital specificity. Commercial apprenticeship graduates are usually considered as workers with rather general human capital. Most commercial workers are white collar workers such as secretaries, clercs or salesmen who can transfer their skills easily. Manufacturing workers in contrast are viewed as workers with rather specific human capital, as manufacturing workers perform very specific technical tasks to produce a particular sort of product (Doeringer and Piore; 1971; Janssen and Pfeifer; 2009). Indeed, many former studies find higher displacement losses for manufacturing workers than for commercial or service workers.

We report fixed effect specifications with additional controls for yearly working days. Table 3.6 and Figure 3.6 show the results for commercial apprenticeship graduates.

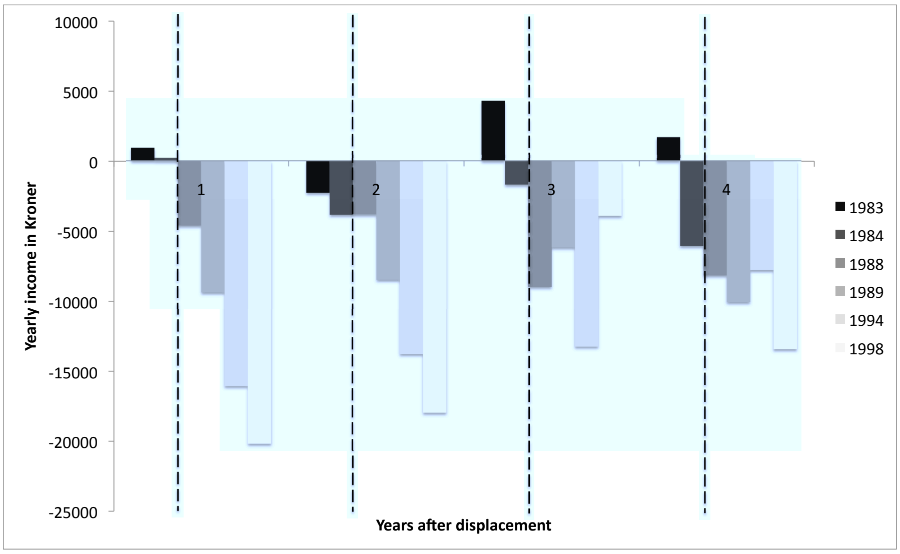

Figure 3.6: Income: Commercial
Note: The bars represent the absolute amount of displacement losses. The dashed line represents the introduction of the flexible wage bargaining system.

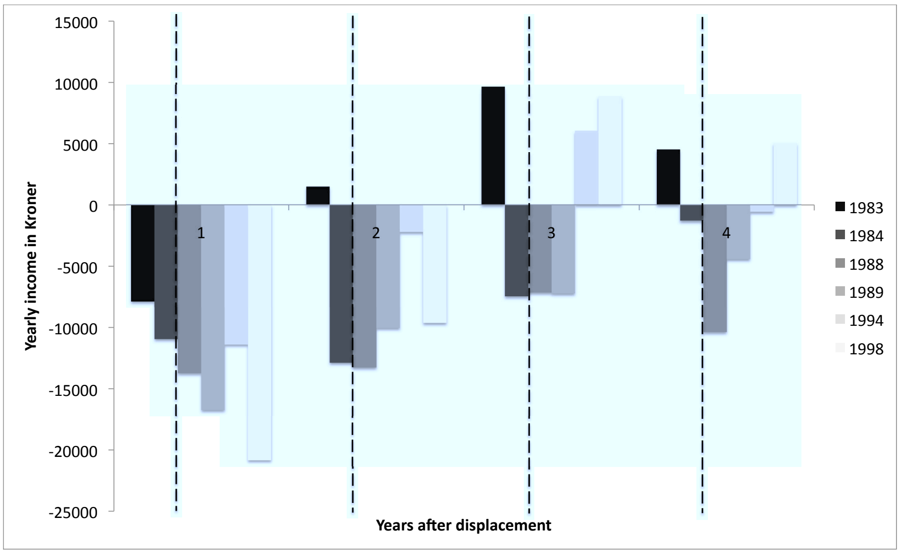

Figure 3.7: Income: Manufacturing
Note: The bars represent the absolute amount of displacement losses. The dashed line represents the introduction of the flexible wage bargaining system.

The pattern looks similar to the results we obtain for the whole sample. Displacement losses for the cohorts of 1983 and 1984 are rather small and insignificant after we control for differences in working days. For the latter cohorts displacement losses start to grow at least for the first two years after displacement and are highest for the cohort of 1999. For the latter cohorts the estimated displacement losses are even somewhat bigger than for the entire sample.

Table 3.6: Displacement losses: Commercial

	Years after displacement: 1	2	3	4
1983 cohort:	977.7274	-2241.553	4305.456	1725.105
1984 cohort:	242.5153	-3827.422	-1660.619	-6050.061 *
1988 cohort:	-4589.795 **	-3797.614 *	-8963.984 ***	-8143.294 **
1989 cohort:	-9355.726 ***	-8451.106 ***	-6141.033 **	-10041.75 ***
1994 cohort:	-16059.49 ***	-13773.79 ***	-13243.52 ***	-7759.367 **
1999 cohort:	-20155.68 ***	-17950.15 ***	-3894.654	-13426.97 *

Note: All data are drawn from the IDA 1980-2004
* Denotes significant at 10 percent level.
** Denotes significant at 5 percent level.
*** Denotes significant at 1 percent level.

Table 3.7: Displacement losses: Manufacturing

	Years after displacement: 1	2	3	4
1983 cohort:	-7877.271	1483.737	9649.177	4507.252
1984 cohort:	-10966.44 *	-12886.49 **	-7451.046	-1286.753
1988 cohort:	-13733.6 **	-13267.74 **	-7143.845	-10394.38 *
1989 cohort:	-16723.3 ***	-10062.95 *	-7219.173	-4417.947
1994 cohort:	-11412.64 *	-2210.99	6032.771	-568.7031
1999 cohort:	-20822 **	-9654.591	8823.77	5028.253

Note: All data are drawn from the IDA 1980-2004
* Denotes significant at 10 percent level.
** Denotes significant at 5 percent level.
*** Denotes significant at 1 percent level.

In order to compare those results to the sample of manufacturing workers Table 3.7 and Figure 3.7 present the results.

The pattern for manufacturing workers contrasts the pattern for commercial workers to some extend. Similar to the commercial workers we do not find no displacement losses for the 1983 cohort. However, for the cohorts from 1984 to 1999 we find big displacement losses for the first year after displacement and smaller displacement losses for the second year after displacement. In the third and fourth year after displacement we almost find no significant displacement losses. One possible explanation for this pattern is that displacement losses of manufacturing workers depend less on the changes in the wage bargaining system than displacement losses of commercial workers. Displacement losses of manufacturing workers might be much stronger related to the loss of specific human rather than to the nature of the wage bargaining system. In contrast commercial workers have more general human capital that is easily transferable across firms. Thus commercial workers might suffer less from the loss of specific human capital but might be much stronger affected by the changes in the wage bargaining system.

To sum up, we have shown that displacement losses are bigger in periods with flexible wages—independent of whether workers are displaced in boom or recession periods. In addition, displacement losses under flexible wages remain substantially even if we control for differences in the labor market attachment which indicates that displacement losses under flexible bargaining systems arise in particular because employers can impose wage penalties on new hires.

3.7 Discussion and conclusion.

In our final section we give a short overview and discussion of the results. The aim of this chapter was to contribute to the literature in two ways. First, we wanted to show how displacement losses vary under different forms of wage bargaining regimes to draw conclusions about the genuine differences in estimated displacement losses between Europe and the US. Second, we wanted to show how displacement losses differ for individuals that perform different types of tasks in different occupations.

With respect to the first objective of this chapter, our findings reveal that displacement losses in the first years after displacement are substantially bigger under flexible wage bargaining systems than under rigid wages. This result holds either for recessions and boom periods. In particular, wage and income losses that are attributed to wage reductions within subsequent firms rose over time. One possible explanation for such a pattern is that employers, under flexible wage bargaining systems, impose wage penalties on new hires (former displaced workers). For example, as wage reductions are often perceived as unfair and demotivating, employers can adjust their costs in economic downturns by paying lower wages to new hires rather than reduce the wages of longer tenured workers. Moreover, as employer learning about new hires is costly, employers can impose wage penalties on those new hires—such penalties might be particularly high if those new hires lost their former jobs due to a reason that is unknown by the employer. Another reason might be that employers are more likely to pay wage premiums or long term incentive wages to internal candidates under flexible wage systems—displaced workers might forgo such bonuses after loosing former jobs. Such processes might induce higher displacement losses under more flexible wage systems, in particular in the first years after displacement when information asymmetries are particularly high.

Moreover, former literature argues that a flexible wage formation process reduces unemployment spells and lay-offs, as wages can be adjusted according to the economic conditions. However, the results for Denmark seem to contradict this view to some degree as not only displacement losses according to wage reductions but also the entire displacement losses—including losses caused by unemployment—rose over time with increasing wage flexibility. One potential explanation for this contradiction is that employment protection was always very low in Denmark—even in the early 1980s when the wage bargaining system was very rigid. Therefore, employers might be less reluctant to pay higher wages because during bad economic conditions employers can easily lay those high paid workers off. Yet, from our investigation we cannot tell whether unemployment would have been higher if Denmark would have stayed with its rigid wage bargaining system.

Therefore, our first major contribution to the literature lies in showing an increase in displacement losses after the transition to a flexible wage bargaining system in Denmark. Former studies only guessed about the relationship between displacement losses and wage flexibility to explain why the empirical literature on displacement losses differs so substantially between Europe and the USA. However, we are the first that are able to show that effect by exploiting an exogenous change in the wage bargaining sytsem. As most European countries have a much more centralized wage bargaining system than the U.S., we provide one plausible explanation why researchers find bigger displacement losses in the U.S. than in most European countries .

With respect to the second objective of the chapter , we show that the transition to a flexible wage bargaining system affects mostly commercial apprentices but not so much apprentices from the manufacturing sector. Such a result indicates that the nature of the wage setting process affects mostly workers with general human capital but not with more firm specific human capital.

Therefore our second contribution is that we show an interaction between the type of human capital, the flexibility of the wage bargaining process and workers displacement losses. Presumably the fact that workers and firms invest together in firm specific human capital and have a higher interest in long term relationships detains firms from exploiting their market power under a more flexible wage bargaining system. Consequently displacement losses of apprentices from the manufacturing sector are much more related to losses of firm specific human capital rather than to the flexibility of the wage bargaining system.

The second and the third chapter of this dissertation investigated different relations between tasks and income. However, income is not the only labor market outcome that drives individuals' behavior in the labor market. In fact, income is only one factor—and for many people not even the most important factor—that people consider when they have to decide which job to choose, how much work effort to impose or whether to work at all. Therefore, research should aim at investigating other labor market outcomes and show how those labor market outcomes are related to the task-based view. The next chapter 4 provides a first step in this direction by investigating the relation between job satisfaction and contents of tasks.

In contrast to the workers income, job satisfaction considers much more aspects of an individuals work life and reveals insights that we cannot obtain by investigating wages or income. In particular the fourth chapter aims at investigating how gender-specific social norms influence the relationship between the performance of different types of tasks and job satisfaction.

Appendix B

B.1 Tables

Table B.1: Descriptive statistics: Displaced workers

Variable	Obs	Mean
Yearly income	81175	150415.500
Working days	81175	250.296
Age	81175	27.686
Female	3388	0.402

Note: All data are drawn from the IDA.

Table B.2: Descriptive statistics: Non-displaced workers

Variable	Obs	Mean
Yearly income	401060	177491.700
Working days	401060	290.983
Age	401060	27.947
Female	16732	0.459

Note: All data are drawn from the IDA.

Chapter 4

Occupational stereotypes, gender segregation and job satisfaction

4.1 Introduction

Despite the great strides towards gender equality in many western countries over the past 50 years, gender segregation remains persistent , with women crowded into lower-paid jobs with worse career prospectives (Kidd and Goninon; 2000; Johnson and Solon; 1996). While earlier literature links gender segregation to theories of employer discrimination, a more recent theory by Akerlof and Kranton (2000) links occupational segregation to gender-specific job stereotypes. Specifically, Akerlof and Kranton (2000) incorporate the sociological concept of identity into an economic framework. They propose a utility function in which identity is associated with different social categories and the ways in which people in these categories are expected to behave. In their model individuals suffer a utility loss if their action does not correspond to gender prescriptions for behavior. Akerlof and Kranton (2000) argue that people in occupations associated with the opposite gender often have ambiguous feelings about their work because they violate their own identity or that of their coworkers. Thus Akerlof and Kranton (2000) argue that gender segregation in the labor market might remain persistent because many people refuse to choose a job stereotypically associated with the opposite gender. In line with this theory, empirical studies in psychology find that individuals strongly stereotype occupations (McCauley and Thangavelu; 1991; Shinar; 1975; White and White; 2006). However, no evidence exists that occupational stereotypes affect the utility and preferences of individuals.

As identity and individual utility are usually impossible to measure, providing empirical evidence showing that occupational stereotypes influence individual utility is difficult. However, we argue that providing evidence on the relationship between self-reported job satisfaction and occupational stereotypes is a first step to more fully understanding how social influences affect gender-specific preferences in the labor market and why gender segregation remains persistent even in countries where women and men have equal rights. Therefore, to estimate the relationship between gender-specific stereotypes and job satisfaction, this paper follows and combines two kinds of empirical literature. First, we follow the economic literature on self-reported job satisfaction, which views self-reported job satisfaction as a sub-utility from working (Clark and Oswald; 1996; Clark; 1997). Second, we extrapolate the strand of psychological literature that uses different kinds of indices to measure occupational stereotypes in the labor market (McCauley and Thangavelu; 1991; Shinar; 1975; White and White; 2006).

Fortunately, we have access to a unique data set that not only allows us to create an index for occupational stereotypes but also contains a variety of categorical job satisfaction measures. The major novelty of our work is that we are the first that can create a ordinal measure of the gender specific stereotypes for individual's job that is representative for the German population. Specifically, we use the German "BiBB/IAB Strukturerhebung," which contains data on 30,000 individuals and is representative for the German workforce. In addition to the job satisfaction measures, the data contains detailed information on each individual's job tasks and a variable that indicates whether the individual considers her or his job to be more appropriate for females or males. We use this information to create a conditional index indicating whether society on average associates each observed individual's job with female or male stereotypes. To our knowledge the BiBB/IAB survey is the only data set containing this kind of information.

Our results reveal structural gender differences in the correlations between occupational gender stereotypes and job satisfaction. They show that women report lower satisfaction values in stereotypically male jobs, an effect most pronounced in satisfaction with work climate and the contents of tasks. One notable exception is income satisfaction, for which women on average report higher values for stereotypically male jobs. In contrast, men report higher satisfaction values in stereotypically male jobs. These results are fairly stable, and we are able to confirm them for a variety of empirical specifications. The results remain robust when we control for unpleasant working conditions such as heavy lifting or night shifts which might predominate in male jobs.

The primary concern with our correlations is that individuals select themselves into female or male jobs for different reasons and are likely to be fairly different in terms of their tastes and abilities. Hypothetically women (men) in stereotypically male (female) jobs may be more likely to favor job characteristics in stereotypically male (female) jobs than women (men) in female (male) jobs. Therefore, pure correlations of the relationship between job satisfaction and occupational stereotypes are likely to underestimate the average effect of performing a job that is related to stereotypes associated with the opposite sex.

We overcome this endogeneity problem by applying an instrumental variable regression. As an instrument we use our index for occupational stereotypes and calculate the average of this index for each individual's region of residence. We argue that any individual living in a region where stereotypically male jobs predominate is more likely to choose a stereotypically male job. Nonetheless, the predominance of stereotypically male jobs should not directly affect the individual's job satisfaction. Our IV estimates confirm our correlations, as we find that men report higher satisfaction values for all satisfaction dimensions in stereotypically male jobs than in stereotypically female jobs. Women, in contrast, report lower satisfaction values. However, when we consider the endogeneity of job choice, our standard errors increase substantially, and the effects remain significant only for satisfaction with work climate.

Our results show a relationship between occupational stereotypes and self-reported job satisfaction. Such a relationship might have far-reaching consequences for policy makers who wish to reduce gender-specific differences in the labor market. In particular, if stereotypes affect the job choice behavior of individuals, then labor market policies such as female quotas, anti-discrimination laws, or company policies aimed at facilitating the combination of work and family life might have little effect on reducing occupational segregation and the resultant gender wage gap.

The remainder of the chapter is structured as follows. Section 3.2 presents a bried literature review. Section 3.3 presents the data set and the construction of our index for occupational stereotypes in detail, and section 3.4 describes the estimation methods. Section 3.5 presents the results, and section 3.6 both concludes and provides and discusses the results in the light of the economic literature.

4.2 Data

This section provides the details of the data and the measurement of our index for occupational stereotypes. For the entire investigation, we use the 1991/92 wave of the Qualification and Career Survey, carried out by the German Federal Institute for Vocational Training ("Bundesinstitut für Berufsbildung") and the Research Institute of the Federal Employment Service (Institut für Arbeitsmarkt- und Berufsforschung). To our knowledge, this wave of the Qualification and Career Survey is the only data set containing a variable that allows the construction of a variable for occupational gender stereotypes. The survey is a representative one percent sample of the German workforce, containing roughly 30,000 observations and a wide range of individual and workplace-related variables.

We restrict our sample to West German residents, for whom there were no missing values in our main variables of interest. This restriction leaves us with 11,660 observations for men and 7,336 observations for women. We choose this restriction because the fall of the Berlin wall in 1989 and the reunification of Germany in 1991 had negative influences on job satisfaction in East Germany, given the tremendous uncertainty of East German workers about their ability to compete in the job market. As Frijters et al. (2004) show, job satisfaction in East Germany was exceptionally low in the years around 1991. The East German industrial sector in particular was badly affected by an economic downturn, with many people in the industry losing their jobs after reunification. As industrial jobs are linked to stereotypically male jobs, the consequences of the reunification might bias our estimates. Subsection 3.1 presents our dependent variables on job satisfaction, subsection 3.2 explains in detail how we construct or measure for gender specific stereotypes, and section 3.3 describes the control variables.

4.2.1 Dependent variables

Our dependent variables measure different dimensions of job satisfaction on a four-point scale ranging from being very unsatisfied to being very satisfied. We argue that such a job satisfaction measure is a valid indicator of an individual's job utility, covering all kinds of factors that are connected to that individual's job. The first variable measures general job satisfaction; the second, measures satisfaction with work climate; the third, satisfaction with the contents of tasks; and the fourth satisfaction with income. The exact questions are as follows[1]:

- *How satisfied are you with your occupational activity, considering every aspect of it?*
- *How satisfied are you with your occupational activity, considering the work climate?*
- *How satisfied are you with your occupational activity, considering the form and content of your tasks?*
- *How satisfied are you with your income?*[2]

Tables 4.1 and 4.2 present descriptive statistics for all satisfaction measures.

Table 4.1: Job satisfaction: Women

Satisfaction dimension	Overall	Work climate	Tasks	Income
Very unsatisfied	1.42	1.96	1.57	4.66
Unsatisfied	6.9	8	8.7	23.69
Satisfied	59.39	51.38	57.84	59.28
Very satisfied	32.29	38.66	31.9	12.36

Note: All data are drawn from the BIBB/IAB Strukturerhebung 1991/92.
Columns contain percentages for men on 4-point Lickert scales.

[1] Some economists worry about the reliability of these kinds of satisfaction measures. Nevertheless, psychologists use these measures widely. Therefore, as Clark and Oswald (1996) argue, we should interpret this use as validating the seriousness of these kinds of investigations. Moreover, these and similar kinds of research are finding increasing acceptance, even within economics (Frey and Stutzer; 2002).

[2] The original german questions are: *Wie zufrieden sind Sie alles in allem mit Ihrer derzeitigen beruflichen Tätigkeit? Sind Sie zufrieden in Ihrer Tätigkeit in Bezug auf: Betriebsklima? Sind Sie zufrieden in Ihrer Tätigkeit in Bezug auf: Art und Inhalt der Tätigkeit? Sind Sie zufrieden in Ihrer Tätigkeit in Bezug auf: Einkommen?*

Table 4.2: Job satisfaction: Men

Satisfaction dimension	Overall	Work climate	Tasks	Income
Very unsatisfied	0.93	1.8	0.81	2.41
Unsatisfied	5.45	8.87	6.99	18.83
Satisfied	63.35	56.08	61.8	65.59
Very satisfied	30.27	33.25	30.4	13.17

Note: All data are drawn from the BIBB/IAB Strukturerhebung 1991/92.
Columns contain percentages for men on 4-point Lickert scales.

All measures show a reasonably typical picture for these kinds of satisfaction measures (see e.g., Blanchflower and Oswald; 2004). Most individuals report being either very satisfied or satisfied. However, a tendency exists for individuals to report lower satisfaction values for their income than for other dimensions of job satisfaction. Only 12 percent of the women and 13 percent of the men are very satisfied with their income. In contrast, 38 percent of the women and 33 percent of the men are very satisfied with their work climate. Women report the highest satisfaction category slightly more often than men. Only for income satisfaction do women report lower values.

Our variable of main interest is an index measuring the socially expected stereotype of a job. The next subsection describes in detail how we construct our stereotype index.

4.2.2 Explanatory variable: occupational stereotypes

In general, creating a valid measure for occupational stereotypes is fairly difficult. In particular, for large and representative data sets, information for creating such a measure is usually not available. Some psychological studies simply use the percentage of females within a certain occupation. However, such an approach might be misleading, as perceived stereotypes might not follow these patterns.

Therefore, we propose calculating a conditional reference measure for occupational gender stereotypes. We argue that our measure displays the majority's gender-specific association of a job and is a valid measure for occupational stereotypes in the German population.

To calculate our index for gender-stereotyped occupations, we rely on a particular variable in our data set. One question asks individuals whether they think that their jobs can be performed only by men, only by women, or by both sexes equally[3]:

- *Can your job be performed equally by men and women if they have the same background?*

The possible answers are "only by a woman," "better by a woman," "equally by women and men," "better by a man" or "only by a man[4]."

Table 4.3 presents descriptive statistics of this variable for women and men separately.

Table 4.3: Occupational sex stereotypes.

Gender:	male	female
only by woman	0.03	3.65
better by woman	0.18	13.31
by man and woman equally	60.28	82.73
better by man	23.61	0.26
only by man	15.89	0.05

Note: All data are drawn from the BIBB/IAB Strukturerhebung 1991/92.
Columns contain percentages for men and women.

Not surprisingly, a fairly low percentage of men say that their own job could not be performed by a man or would be performed better by a woman. However, about 4 percent of all females say that their jobs could not be performed by a man at all, and about 13 percent believe that it would be better performed by a woman. In contrast, about 40 percent of all men report that their jobs could not be performed by women or performed as well by women.

To describe the occupation of an individual, we use detailed information on the tasks that an individual performs. Participants were asked to mark on a list what kinds of tasks

[3]Similar measures are quite common in the psychological literature investigating the sexual stereotypes of occupations (White et al.; 1998). However, most of these measures are conducted in small samples.

[4]The original german question is: *Kann Ihre Tätigkeit von einem Mann und von einer Frau gleich gut ausgeübt werden, wenn sie über due notwendige Ausbildung verfügen? The original german answers are:* Von Frauen und Männern gleich gut Nur von einer Frau Eher von einer Frau Eher von einem Mann Nur von einem Mann

they have to perform in their jobs. We report the descriptive statistics on the task measures separately for women and men in the appendix. This information helps us to construct a valid measure for occupational stereotypes.

To create the index, we first run a regression of the following form:

$$p_i = T_i\lambda + \varepsilon_i \tag{4.1}$$

where p_i is the variable on gender job stereotypes which is 0 when the job is viewed as most appropriate for females and 4 if it is most appropriate for males. T_i is a vector containing a set of dummies for all of our task indicators. λ is the respective coefficient vector and ε the error term.

In Table **??** in the appendix we show the results of the regression according to equation 4.1. Table **??** shows that nearly all tasks enter highly significantly into the regression, indicating that tasks are a core determinant for occupational stereotypes. Tasks such as dealing with machines, driving vehicles, or supervising personnel show positive significant values, indicating that people on average view such tasks as stereotypically male. Tasks such as cleaning, care-giving, or teaching show negative significant coefficient values, indicating that people on average view such tasks as stereotypically female.

To construct our index, we obtain the predicted values from equation 4.1 ($P_i : \hat{p}_i = T_i\hat{\lambda}$). P_i will give us a proper indicator for occupational gender stereotypes persistent in society because the index measures the average occupational stereotype of an individual's job. For example, a job in which an individual performs tasks such as preparing food, serving and accommodating, cleaning, disposing garbage, buying and selling, writing, teaching and care taking leads to a value of $P_i = 0.95$. In contrast, a job with tasks such as repairing, driving and working on buildings lead to a value of $P_i = 3.5$. Therefore, our index indicates that the first job is a stereotype female job because 0.95 is a rather lower value of P_i whereas the second job is a stereotype male job because of a high value of P_i.

4.2.3 Control variables

In addition to our variables of main interest, our data set contains a variety of individual and job characteristics allowing us to control for influences on job satisfaction, influences not directly related to occupational stereotypes. We observe an individual's age in years, and we create a categorical variable for the worker's type of education. The first category of the education variable contains low-educated people such as those with no university or apprenticeship degree. The second category contains medium-educated people with an apprenticeship degree, and the third contains high-educated people with a university degree[5].

In addition, we observe weekly working hours and monthly income, which we observe in 16 categories. We assign midpoints to these income categories and treat the variable as continuous, as DiNardo and Pischke (1997) did when using this data. We are also able to observe certain job characteristics, not usually observable in most data sets. We know whether a worker carries or lifts heavy weights, works in wet and cold or smoky and dusty/dirty/noisy surroundings, and whether she or he works in unhealthy physical positions or works night shifts. These control variables are likely to strongly correlate with a person's job satisfaction, and our results bear out this assumption. Descriptive statistics on all the variables appear in the appendix.

[5]Apprenticeship training in Germany combines on-the-job training and formal education. Around 60 percent of each cohort choose apprenticeship training. In contrast, university graduates compose about 20 percent, a small percentage in comparison to other Western countries.

4.3 Estimation strategy

This section presents our estimation strategy. A number of studies such as Clark and Oswald (1996), consider job satisfaction as a type of sub-utility function u representing utility from working in an overall utility function $v = v(u, \mu)$, where μ is utility from other areas of life. The utility from working is usually considered to be of the form:

$$u_i = u_i(w, h, i, j) \tag{4.2}$$

where w is income, h is hours of work, and i and j are sets of individual and job-specific characteristics. We extend this utility function by a parameter P, which represents the occupational specific stereotypes of an individual's job.

$$u_i = u_i(w, h, i, j, P) \tag{4.3}$$

Therefore, equation (4.2) gives us a natural starting point for applying the following regression equation:

$$JS_i^* = \beta_0 + \beta_1 P_i + \beta_2 w_i + \beta_3 h_i + X_i'\gamma + \varepsilon_i \tag{4.4}$$

JS_i^* is a latent variable that indicates the job satisfaction of individual i. P_i represents our index for gender stereotypes. Bigger values of P_i that are closer to a value of 4 indicate stereotypically male jobs, and lower values of P_i that are closer to a value of 0 indicate stereotypically female jobs. w_i refers to an individual's monthly income, and h_i represents the weekly working hours. X_i contains a broad set of control variables for personal and job characteristics. Our coefficient of main interest is β_1, which measures the effect of being in a stereotypically male job. We estimate equation (4.4) separately for males and females. A positive value of β_1 indicates that females or males report higher satisfaction values for stereotypically male jobs. A negative value of β_1 indicates that females or males report lower satisfaction values for stereotypically male jobs.

As JS_i^* is not observable, we follow the literature by assuming the following relationship:

$$JS_i = \begin{cases} 1 & \text{if } JS_{i_i}^* < \alpha_1 \\ 2 & \text{if } \alpha_1 \leq JS_{i_i}^* < \alpha_2 \\ 3 & \text{if } \alpha_2 \leq JS_{i_i}^* < \alpha_3 \\ 4 & \text{if } \alpha_3 \leq JS_{i_i}^* \end{cases}$$

JS_i is a 4-point Lickert scale index that indicates the satisfaction of individual i, and α_i represents cut parameters which we then estimate. As ε_i is assumed to be normally distributed, we apply an ordered probit model.

Thus far equation (4.4) does not take into account that individuals are not randomly assigned to their jobs but instead choose them according to their preferences, their abilities, and their employer's hiring decisions. Individuals who perform jobs associated with stereotypes of the opposite gender are either likely to favor those jobs or are able to deal with the potential negative consequences arising from gender-specific stereotyping. Thus β_1 is likely to underestimate the true average effect of occupational stereotypes on the individual's job satisfaction. We handle this problem by using an instrumental variable approach. We estimate the following equation in the first stage.

$$P_i = \delta_0 + \delta_1 Z_i + X_i' \varphi + u_i \tag{4.5}$$

Equation (4.5) models the self-selection alongside the ordered probit model. Again, P_i is the index for occupational stereotypes. X_i contains the same set of variables such as in (4.4). Z_i is a instrumental variable that we assume to be correlated with P_i but not with ε_i.

As an instrument we use the mean of P_i calculated at the state level of the individuals residence. The logic is as follows: If an individual happens to live in a state with a high percentage of stereotypically male jobs, she or he is more likely to choose a stereotypically male job, In particularly because individuals in Germany are much less mobile than in the U.S. and often choose a job in their region of residence. Consequently for most individuals the region of residence is given by their region of birth and can be considered as exogenously given for most individuals. However, the percentage of stereotypically male jobs in an individual's region should not directly affect the individuals job satisfaction. German states have a high variation in their industry and urbanization. Some states constitute only a large city such as Berlin, where urbanization is quite high and where service jobs, which are usually considered stereotypically female, predominate. Other states cover several cities and larger regions, where the agricultural sector and industries such as coal mining, which are more likely to be perceived as stereotypically male, predominate. For the purpose of our study we calculate the mean of P_i in each state separately for women and men.

We are aware that such an instrument does not mimic a fully exogenous randomization of an individual's job choice. Instead, our instrument rather identifies a restriction in job choices for a particular sub-population. Therefore, we are able to identify only a local average treatment (LATE) for a particular sub population (Imbens and Angrist; 1994). Finding an instrument or a natural experiment that identifies a true randomization for an individuals job choice is practically impossible for the data at hand. However, we argue that the LATE offers important insights still as we are able to identify a sub-population of individuals who did not choose their jobs according to their preferences but rather because the job was available within the individual's region. Such individuals are far less likely to choose their jobs because they have extensive preferences for stereotypically female or male jobs[6].

We estimate our regression in a two-stage procedure similar to the two-stage conditional maximum likelihood approach proposed by Rivers and Vuong (1988). First, we obtain $\hat{u}_i = P_i - Z_i'\hat{\delta}$ from equation (4.5). Second, we estimate the following regression with an ordered probit model.

$$JS_i^* = \beta_0 + \beta_1 P_i + \beta_2 w_i + \beta_3 h_i + X_i'\gamma + \theta\hat{u}_i + \varepsilon_i \tag{4.6}$$

Equation (4.6) is similar to equation (4.4) but additionally contains the regressors $\hat{u}_i$. θ is referred to as the additional coefficient of $\hat{u}_i$. A useful feature of this procedure is

[6]There is extensive discussion in the literature about the use and interpretation of the LATE (Imbens; 2010).

that the z-statistics of θ serves as a test for the exogeneiety of P_i. The null hypothesis that P_i is exogenous has to be rejected if $\theta \neq 0$. However, obtaining the standard errors from such a procedure directly leads to misleading conclusions, as the naive standard errors do not take into account that the first stage is estimated with bias. Thus we adjust the errors according to Murphy and Topel (1985), who derive the standard errors for an IV probit estimator with a continuous endogenous regressor. We extend their approach to an IV ordered probit regression with a continuous endogenous regressor.

4.4 Results

This section presents the regression results in detail, first giving the descriptive statistics, and, second the results for the ordered probit regression. Third, we present the results of our 2SCML IV approach, and fourth, we present some robustness checks.

4.4.1 Descriptive statistics

Table 4.4 provides some descriptives statistics for P_i, our index for occupational stereotypes, to determine how occupational stereotypes are distributed across the observed population. If P_i is closer to 4, the value indicates that the job is associated with a more male stereotype. If P_i is closer to 0, then the job is associated with a more female stereotype. The first row of the table shows an average of P_i for men of about 2.40 and a variance of about 0.38. For women the respective values are 2.03 and 0.26. Thus the results show that men work significantly more often in stereotypically male jobs and indicate a tendency of occupational segregation along the lines of occupational stereotypes. But the variance of P_i is bigger for men than for women, meaning that men work in a broader range of jobs than women.

Table 4.4: Index: Stereotype P

Gender:	Mean	Std. Dev.
Women	2.03	0.26
Men	2.41	0.38
Education:	Mean	Std. Dev.
Low	2.25	0.38
Middle	2.30	0.40
High	2.11	0.27

Note: All data are drawn from the BIBB/IAB Strukturerhebung 1991/92.
Predicted values from an OLS regression of occ. sex stereotypes on tasks.

The second part of the table shows the means and standard deviations for the three educational groups. For all three groups we find a mean slightly above 2. For university graduates the table shows the lowest mean of about 2.11 and the smallest standard deviation of about 0.27. The tendency towards stereotypically male jobs is most pronounced among apprenticeship graduates, who account for the biggest percentage of the German work force. However, apprenticeship graduates also have the biggest variance for occupational stereotypes. Such a result is not surprising because apprenticeship graduates are most likely to hold a broad range of jobs. The apprenticeship degree qualifies its recipients for stereotypically female jobs such as service jobs and for stereotypically male jobs such as blue-collar jobs.

Table 4.5 and 4.6 show means and standard deviations of our index for occupational stereotypes P_i by satisfaction levels for women and men. Table 4.5 shows the results for women. Those women who are very unsatisfied with their jobs are most likely to work in stereotype male jobs—i.e. the value of P_i is with 2.7 highest for women who are very unsatisfied with their jobs. The table shows a similar result for satisfaction with work climate and satisfaction of tasks. The average of P_i is 2.06 for women who are very unsatisfied with their work climate and 2.08 for women who are very unsatisfied with the contents of their tasks. The only exception is income satisfaction, where the mean of P_i is with 2.05. Thus the pure descriptive results indicate that women who work in stereotypically male jobs are more satisfied with their income but less satisfied with their overall satisfaction, with their work climate and their contents of tasks.

Table 4.5: Stereotypes by satisfaction categories: women

Satisfaction dimension	Overall	Work climate	Tasks	Income
Very unsatisfied	2.07	2.06	2.08	1.98
Unsatisfied	2.03	2.04	2.05	2.02
Satisfied	2.04	2.04	2.04	2.04
Very satisfied	2.03	2.02	2.02	2.05

Note: All data are drawn from the BIBB/IAB Strukturerhebung 1991/92.
Columns contain means of P_i for each satisfaction category.

Table 4.6 shows the results for men. The evidence for men does not show such a clear picture. We find a tendency that men who report lower values for overall satisfaction, satisfaction with tasks, and satisfaction with income are more likely to work in stereotypically male jobs. Only men who report being very satisfied with their work climate work are slightly more often in stereotypically male jobs.

Table 4.6: Stereotypes by satisfaction categories: men

Satisfaction dimension	Overall	Work climate	Tasks	Income
Very unsatisfied	2.37	2.38	2.44	2.39
Unsatisfied	2.44	2.39	2.43	2.43
Satisfied	2.42	2.41	2.43	2.41
Very satisfied	2.36	2.41	2.36	2.38

Note: All data are drawn from the BIBB/IAB Strukturerhebung 1991/92.
Columns contain means of P_i for each satisfaction category.

4.4.2 Ordered probit estimates

Table 4.7 provides the estimates of equation (4.4)—the simple ordered probit regression of the relation between stereotypes and job satisfaction for women and men. The dependent variables are our four satisfaction measures: overall job satisfaction, satisfaction with work climate, satisfaction with the contents of tasks, and satisfaction with income. Our main variable of interest is P_i, our index for gender-specific stereotypes. A positive value of β_1 indicates that the probability of being in the highest satisfaction category rises while the probability of being in the lowest category decreases.

Table 4.7 presents the estimates for women, with additional controls typically included in studies on job satisfaction. Before we discuss the effect of occupational stereotypes, we show that the control variables yield results in line with previous literature. Income has a positive significant effect on overall job satisfaction, satisfaction with the contents of tasks, and income satisfaction. This result is in line with the literature on job satisfaction (Clark and Oswald; 1996; Clark; 1997; Frijters et al.; 2004). In contrast, the satisfaction with work climate decreases for women with a higher income. As more competitive environments are likely to yield higher income, this result is in line with recent findings that women face disadvantages under strong competition (Gneezy et al.; 2003). Job satisfaction decreases with age at a decreasing rate. The coefficients on age and age-squared show the typical U-shaped pattern found in the former literature. However, the coefficients are not significant at the 10 percent level. Weekly working hours shows the typical negative effect on job satisfaction. In contrast to some previous findings, individuals with higher education report higher job satisfaction values. Nevertheless, other studies such as Blanchflower and Oswald (2004) find the same positive significant effect for education.

Table 4.7: Job satisfaction and occupational stereotypes: women

Dependent variables:	Overall	Work climate	Tasks	Income
Index: Stereotypes *P*	-0.047	-0.127**	-0.209***	0.241***
	(0.052)	(0.051)	(0.051)	(0.053)
Ref.: Low education				
Medium education	0.255***	0.147***	0.325***	0.056*
	(0.032)	(0.031)	(0.032)	(0.031)
High education	0.290***	0.116**	0.449***	-0.006
	(0.048)	(0.046)	(0.048)	(0.047)
Age in years	-1.070	-0.635	0.351	-0.329
	(0.861)	(0.841)	(0.834)	(0.836)
Age squared	1.450	0.407	-0.167	1.026
	(1.038)	(1.020)	(1.008)	(1.011)
Monthly income/100	0.013***	-0.003*	0.012***	0.025***
	(0.002)	(0.001)	(0.002)	(0.002)
Weekly working hours	-0.008***	-0.004**	-0.001	-0.017***
	(0.002)	(0.002)	(0.002)	(0.002)
N	7336	7336	7336	7336

Note: All data are drawn from the BIBB/IAB Strukturerhebung 1991/92.
The dependent variables are 4-point Lickert scales on 4 job satisfaction dimensions.
Robust standard errors are used. Standard errors under coefficients.
* Denotes significant at 10 percent level.
** Denotes significant at 5 percent level.
*** Denotes significant at 1 percent level.

The effect of main interest is the indicator for occupational stereotypes. The sign of P_i is negative for overall satisfaction, satisfaction with work climate and satisfaction with contents of tasks. For satisfaction with income the effect is positive, even if we control for monthly income. While for overall satisfaction the effect is not significant at the 10 percent level, we find well-defined effects with small standard errors for the other satisfaction categories. Therefore, our results support the descriptive statistics section 3.1

As our index does not provide a natural way of interpreting the effect in terms of marginal effects, we show predicted probabilities for two sample jobs. The first job F is stereotypically female and the second job M is stereotypically male. The stereotypically female job F contains the following tasks: preparing food, serving and accommodating, cleaning, disposing of garbage, buying and selling, writing, teaching, and care-taking. According to our index job F, has a value of $P_i = 0.95$. The stereotypically male job M contains the following tasks: repairing, driving, and working on buildings. M has an index value of about $P_i = 3.5$. We hold all other control variables constant at the mean.

Table 4.8 provides the predicted probabilities for being very satisfied for both jobs. We estimate for the stereotypically female job F a probability of about 34 percent of being very satisfied for overall job satisfaction. A women who performs the stereotypically male job has only a 29 percent probabilty of being very satisfied overall. This amounts to a 4 percent decrease in the probability of being very satisfied with overall satisfaction. For the satisfaction with work climate the decrease is 12 per cent and for satisfaction with the contents of tasks the decrease is 18 per cent. Thus for both categories the decrease is even bigger than for overall satisfaction. Only for the satisfaction with income does the effect go in the opposite direction and we estimate a 12 percent increase in the probability of a woman being very satisfied in the stereotypically male job rather than in the stereotypically female job.

Table 4.8: Predicted probability of being very satisfied: women I

Dependent variables:	Overall	Work climate	Tasks	Income
without add. controls[a]				
Stereotypically female job (F):	0.34	0.43**	0.39***	0.07***
Stereotypically male job (M):	0.29	0.31	0.21	0.19
with add. controls[b]				
Stereotypically female job (F):	0.32	0.43*	0.37**	0.07***
Stereotypically male job (M):	0.32	0.32	0.23	0.19

Note: All data are drawn from the BIBB/IAB Strukturerhebung 1991/92.
The dependent variables are 4-point Lickert scales on 4 job satisfaction dimensions.
Predictions stem from regressions of Table 7 and 9
a Contains Education, age, income and working hours as controls.
b Contains *a* and dummies for heavy weight, smoke, dust noise, cold and night shift as controls.
* Difference to male job significant at 10 percent level.
** Difference to male job significant at 5 percent level.
***Difference to male job significant at 1 percent level.

One argument that our results are not caused by gender stereotyping is that male jobs are characterized by challenging physical working conditions (e.g. heavy lifting) that have a strong effect on women's job satisfaction. In other words, the negative effect of performing a stereotypically male job might arise only because women find such working conditions unpleasant. Fortunately, we have detailed information on such working conditions and can control for those influences. Table 4.9 presents the results for the coefficients and shows no major differences with respect to sign and significance level. Table 4.8 shows the predicted probabilities of being very satisfied. The differences between the stereotypically female and the stereotypically male job vanish for overall satisfaction. For satisfaction with work climate, we estimate a 12 percent gap; for satisfaction with contents of tasks, we estimate a 14 percent gap; and for income satisfaction, we estimate a 12 per cent gap. As the results remain quite stable when we include controls for unpleasant work characteristics, we conclude that those characteristics are not driving our results substantially.

Table 4.9: Job satisfaction and occupational stereotypes: women II

Dependent variables:	Overall	Work climate	Tasks	Income
Index: Stereotypes *P*	-0.003	-0.101*	-0.149***	0.243***
	(0.054)	(0.052)	(0.053)	(0.054)
Ref.: Low education				
Medium education	0.215***	0.114***	0.289***	0.028
	(0.032)	(0.031)	(0.032)	(0.031)
High education	0.268***	0.097**	0.429***	-0.022
	(0.049)	(0.046)	(0.048)	(0.047)
Age in years	-0.873	-0.483	0.510	-0.160
	(0.867)	(0.844)	(0.834)	(0.838)
Age squared	1.175	0.181	-0.390	0.800
	(1.047)	(1.024)	(1.009)	(1.012)
Monthly income/100	0.012***	-0.004***	0.011***	0.024***
	(0.002)	(0.001)	(0.002)	(0.002)
Weekly working hours	-0.006***	-0.002	0.001	-0.015***
	(0.002)	(0.002)	(0.002)	(0.002)
Heavy weight	-0.097**	-0.089*	0.002	-0.237***
	(0.047)	(0.045)	(0.044)	(0.046)
Smoke, dust, etc.	-0.257***	-0.186***	-0.268***	-0.129***
	(0.036)	(0.035)	(0.035)	(0.035)
Night-/shiftwork	-0.159***	-0.163***	-0.135***	-0.084**
	(0.038)	(0.037)	(0.038)	(0.037)
N	7336	7336	7336	7336

Note: All data are drawn from the BIBB/IAB Strukturerhebung 1991/92.
The dependent variables are 4 point lickert scales on 4 job satisfaction dimensions.
Robust standard errors are used. Standard errors under coefficients.
* Denotes significant at 10 percent level.
** Denotes significant at 5 percent level.
*** Denotes significant at 1 percent level.

Unfortunately, we do not know how many men work with the observed women. Thus determining whether the effect stems from stereotyping or from the possibility that women do not like to work with men, even in a female job is difficult. We try to overcome this problem by estimating the share of men for each individual's job. In particular we estimate a linear probability model with a gender dummy as dependent variable and the tasks as explanatory variables. We then incorporate the predicted values from that regression into equation (4.4) as an additional control variable.

Table 4.10 presents the results for women. It shows negative coefficient values for P_i with respect to overall satisfaction, satisfaction with work climate, and satisfaction with contents of tasks. It also shows a positive effect for income satisfaction. The effect is statistically significant for overall satisfaction and satisfaction with contents of tasks. For work climate we estimate a very similar coefficient value as in Table 4.9, but the standard errors become somewhat bigger. The newly incorporated variable "percentage of males" is positive significant for overall satisfaction, satisfaction with contents of tasks, and income satisfaction. The effect is negative but not significant for the satisfaction with work climate. Therefore, these results confirm, at least qualitatively, the results in Table 4.9 . However, we are aware that multicollinearity might bias the results of Table 4.10 and even turn the coefficient signs in the wrong direction, as P_i and the estimated percentage of males within each job are highly correlated—the correlation of both variables is about 0.81. Therefore, we emphasize that the results in Table 4.10 must be carefully interpreted.

Table 4.10: Job satisfaction and occupational stereotypes: women III

Dependent variables:	Overall	Work climate	Tasks	Income
Index: Stereotypes *P*	-0.364***	-0.101	-0.660***	0.051
	(0.090)	(0.088)	(0.090)	(0.092)
Percentage of males	0.537***	-0.001	0.757***	0.285***
	(0.108)	(0.106)	(0.108)	(0.106)
Ref.: Low education				
Medium education	0.209***	0.114***	0.280***	0.025
	(0.032)	(0.031)	(0.032)	(0.031)
High education	0.237***	0.098**	0.386***	-0.039
	(0.049)	(0.046)	(0.049)	(0.047)
Age in years	-1.033	-0.483	0.290	-0.248
	(0.873)	(0.845)	(0.840)	(0.838)
Age squared	1.413	0.181	-0.060	0.932
	(1.055)	(1.026)	(1.017)	(1.013)
Monthly income/100	0.010***	-0.004**	0.008***	0.022***
	(0.002)	(0.002)	(0.002)	(0.002)
Weekly working hours	-0.006***	-0.002	0.002	-0.015***
	(0.002)	(0.002)	(0.002)	(0.002)
Heavy weight	-0.089*	-0.089*	0.014	-0.233***
	(0.047)	(0.045)	(0.044)	(0.046)
Smoke, dust, noise, etc.	-0.267***	-0.186***	-0.283***	-0.135***
	(0.036)	(0.035)	(0.035)	(0.035)
Night-/shiftwork	-0.136***	-0.164***	-0.104***	-0.073*
	(0.038)	(0.037)	(0.038)	(0.037)
N	7336	7336	7336	7336

Note: All data are drawn from the BIBB/IAB Strukturerhebung 1991/92.
The dependent variables are 4-point Lickert scales on 4 job satisfaction dimensions.
Robust standard errors are used. Standard errors under coefficients.
* Denotes significant at 10 percent level.
** Denotes significant at 5 percent level.
*** Denotes significant at 1 percent level.

Table 4.11 presents the first ordered probit results for men. As we did with women, we look first at the control variables, finding three main differences between the results for men and women. First, age enters the regression as highly significant negative for satisfaction with work climate, the contents of tasks, and income satisfaction. Thus older men seem to report lower satisfaction values than younger men. This result contradicts the result for the women were age does not enter the regressions significantly. Second, income shows a positive effect on all satisfaction measures, including work climate. The result contradicts our previous findings for women who are less satisfied with their work climate if they earn more. However, the result is in line with former evidence showing that men suffer less from competition, which is more likely to occur in well-paid positions. Third, the weekly working hours show no effect or a positive significant effect on satisfaction with the contents of tasks. Such a result might occur because men on average do not differ substantially in their working hours. Men might also put less value on work-time flexibility and therefore remain unaffected by long working hours.

The effect of the main variable of interest P_i shows a more heterogeneous picture than in the case of women. We find a negative significant effect on overall satisfaction and no statistical significant effect for satisfaction with work climate or the contents of tasks. However, in line with the women's results, the effect is positive and significant for income satisfaction. Thus far, the multivariate estimates mimic the descriptive results.

Table 4.11: Job satisfaction and occupational stereotypes: men I

Dependent variables:	Overall	Work climate	Tasks	Income
Index: Stereotypes *P*	-0.094***	0.041	-0.048	0.116***
	(0.031)	(0.030)	(0.031)	(0.031)
Ref.: Low education				
Medium education	0.249***	0.081***	0.295***	0.054*
	(0.031)	(0.030)	(0.031)	(0.031)
High education	0.276***	0.051	0.346***	-0.042
	(0.043)	(0.041)	(0.043)	(0.042)
Age in years	-1.089	-3.269***	-1.475**	-2.436***
	(0.754)	(0.723)	(0.748)	(0.733)
Age squared	1.245	3.527***	1.817**	3.241***
	(0.880)	(0.843)	(0.870)	(0.853)
Monthly income/100	0.013***	0.002*	0.015***	0.025***
	(0.001)	(0.001)	(0.001)	(0.001)
Weekly working hours	0.001	-0.000	0.006***	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)
N	11660	11660	11660	11660

Note: All data are drawn from the BIBB/IAB Strukturerhebung 1991/92.
The dependent variables are 4-point Lickert scales on 4 job satisfaction dimensions.
Robust standard errors are used. Standard errors under coefficients.
* Denotes significant at 10 percent level.
** Denotes significant at 5 percent level.
*** Denotes significant at 1 percent level.

Table 4.12 reports the predicted probabilities for men holding the sample stereotypically female job F and for men holding the stereotypically male job M. For men we estimate an 8 percent decrease for overall satisfaction when switching from the female job F to the male job M. We estimate a 3 percent increase for satisfaction with work climate, a 4 percent decrease for satisfaction with contents of tasks, and a 6 percent increase for income satisfaction. Thus our results show an even bigger negative effect of P_i on men's overall satisfaction than on women's. However, the negative effect for the satisfaction with contents of tasks is much bigger for women and the effect on work climate is even positive, although insignificant.

Table 4.12: Predicted probability of being very satisfied: men

Dependent variables:	Overall	Work climate	Tasks	Income
without add. controls[a]				
Stereotypically female job (F):	0.34**	0.31	0.32	0.09***
Stereotypically male job (M):	0.26	0.34	0.28	0.15
with add. controls[b]				
Stereotypically female job (F):	0.26**	0.25***	0.25**	0.07***
Stereotypically male job (M):	0.33	0.40	0.33	0.17

Note: All data are drawn from the BIBB/IAB Strukturerhebung 1991/92.
Predictions stem from regressions of Table 11 and 13.
The dependent variables are 4-point Lickert scales on 4 job satisfaction dimensions.
a Contains Education, age, income and working hours as controls.
b Contains *a* and dummies for heavy weight, smoke, dust noise, cold and night shift as controls.
* Difference to male job significant at 10 percent level.
** Difference to male job significant at 5 percent level.
***Difference to male job significant at 1 percent level.

Table 4.13 adds further controls for unpleasant working conditions for men. In contrast to the women's results, those for men change substantially when we include the variables for unpleasant working conditions. All coefficients turn positive and highly significant. As we show in Table 4.12, the now positive effects are substantial. For overall satisfaction, we estimate a 6 percentage increase. For satisfaction with work climate, we estimate a 14 percent increase. For satisfaction with contents of tasks, we estimate an 8 percent increase, and for income satisfaction we estimate a 10 percent increase. In contrast to the estimation results for women the results for men are strongly driven by unpleasant working conditions, and when we control for such conditions, men report even higher satisfaction values in stereotypically male jobs than in stereotypically female jobs. This result strongly supports that stereotypes might indeed influence the satisfaction of male workers. In other words, men suffer from the unpleasant working conditions in male jobs but as soon as we control these factors male workers appear to be more satisfied when working in a male job.

Table 4.13: Job satisfaction and occupational stereotypes: men II

Dependent variables:	Overall	Work climate	Tasks	Income
Index: Stereotypes *P*	0.074**	0.156***	0.089**	0.223***
	(0.035)	(0.034)	(0.035)	(0.035)
Ref.: Low education				
Medium education	0.228***	0.061**	0.270***	0.044
	(0.031)	(0.030)	(0.032)	(0.031)
High education	0.210***	-0.003	0.282***	-0.075*
	(0.044)	(0.041)	(0.043)	(0.042)
Age in years	-0.790	-2.988***	-1.138	-2.383***
	(0.755)	(0.726)	(0.750)	(0.734)
Age squared	0.892	3.193***	1.413	3.178***
	(0.882)	(0.847)	(0.873)	(0.853)
Monthly income/100	0.011***	0.000	0.013***	0.024***
	(0.001)	(0.001)	(0.001)	(0.001)
Weekly working hours	0.002	0.001	0.008***	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)
Heavy weight	-0.079***	-0.031	-0.080***	-0.149***
	(0.028)	(0.027)	(0.027)	(0.027)
Smoke, dust, etc.	-0.212***	-0.149***	-0.145***	-0.075***
	(0.028)	(0.027)	(0.028)	(0.027)
Night-/shiftwork	-0.129***	-0.149***	-0.192***	0.006
	(0.026)	(0.025)	(0.026)	(0.026)
N	11660	11660	11660	11660

Note: All data are drawn from the BIBB/IAB Strukturerhebung 1991/92.
The dependent variables are 4-point Lickert scales on 4 job satisfaction dimensions.
Robust standard errors are used. Standard errors under coefficients.
* Denotes significant at 10 percent level.
** Denotes significant at 5 percent level.
*** Denotes significant at 1 percent level.

In Table 4.14 we additionally control for the estimated percentage of males. When we control for percentage of males the coefficients of P_i turn negative significant for overall satisfaction and satisfaction with contents of tasks and remains positive significant for the satisfaction with work climate. The effect remains positive significant for income satisfaction. Apart for the satisfaction with work climate, the coefficients for the estimated percentage of males enters every regression positive and significant. For satisfaction with work climate the coefficient is negative but not significant. Thus Table 4.14 supports our argumentation that stereotypes drive the results and not necessarily the fact that men are working with other men. Again, we report these estimates with caution because of the multicolinearity problem that we previously mentioned.

Table 4.14: Job satisfaction and occupational stereotypes: men III

Dependent variables:	Overall	Work climate	Tasks	Income
Index: Stereotypes *P*	0.009	0.190***	-0.115**	0.284***
	(0.053)	(0.051)	(0.052)	(0.052)
Share of males	0.131	-0.070	0.413***	-0.123
Ref.: Low education				
	(0.083)	(0.078)	(0.082)	(0.079)
Medium education	0.226***	0.062**	0.264***	0.046
	(0.031)	(0.030)	(0.032)	(0.031)
High education	0.206***	-0.001	0.268***	-0.071*
	(0.044)	(0.041)	(0.044)	(0.043)
Age in years	-0.821	-2.973***	-1.237*	-2.357***
	(0.755)	(0.726)	(0.750)	(0.734)
Age squared	0.938	3.170***	1.557*	3.138***
	(0.882)	(0.847)	(0.872)	(0.854)
Monthly income/100	0.011***	0.001	0.012***	0.025***
	(0.001)	(0.001)	(0.001)	(0.001)
Weekly working hours	0.002	0.001	0.007***	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)
Heavy weight	-0.076***	-0.033	-0.071**	-0.152***
	(0.028)	(0.027)	(0.027)	(0.028)
Smoke, dust, etc.	-0.215***	-0.148***	-0.153***	-0.073***
	(0.028)	(0.027)	(0.028)	(0.027)
Night-/shiftwork	-0.128***	-0.150***	-0.188***	0.005
	(0.026)	(0.025)	(0.026)	(0.026)
N	11660	11660	11660	11660

Note: All data are drawn from the BIBB/IAB Strukturerhebung 1991/92.
The dependent variables are 4-point Lickert scales on 4 job satisfaction dimensions.
Robust standard errors are used. Standard errors under coefficients.
* Denotes significant at 10 percent level.
** Denotes significant at 5 percent level.
*** Denotes significant at 1 percent level.

4.4.3 2SCML estimates

One of our greatest concerns with the results thus far is that we implicitly assume that the job choice of an individual is exogenous. Such an assumption is far from reality, as individuals choose their jobs as a result of their tastes or abilities or the hiring decisions of employers. In our case, it is particularly likely that people who decide to perform a job related to stereotypes of the opposite gender can cope far better with the negative effects that arise from stereotyping than can individuals who refuse to perform such a job. As a result, we cannot assume that P_i is an exogenous regressor in equation (4.4).

For this reason we apply a IV regression as described in equation (4.6). Table 4.15 provides the results for women. At the bottom of the table we report the z-statistics of θ, which indicate whether P_i is endogenous or not. The z-value is 1.57 for overall satisfaction, 3.00 for satisfaction with work climate, 1.90 for satisfaction with contents of tasks, and 0.93 for income satisfaction. We have to reject the hypothesis of P_i being endogenous for the estimates for satisfaction with work climate and contents of tasks. Only with respect to overall satisfaction and income satisfaction do we not find that θ is significant at the 10 percent level. However, the z-value is quite close to the critical value of 10 percent for overall satisfaction.

Table 4.15: Job satisfaction and occupational stereotypes: women (2SCML)

Dependent variables:	Overall	Work climate	Tasks	Income
Index: Stereotypes *P*	-2.308	-4.492*	-2.979	-1.08
	(1.985)	(2.31)	(2.076)	(1.5)
Coef. Instrument	0.863**	0.863**	0.863**	0.863**
	(0.287)	(0.287)	(0.287)	(0.287)
z-statistic: θ	1.57	3.00	1.90	0.93
F-statistic: first stage	9.04	9.04	9.04	9.04
N	7336	7336	7336	7336

Note: All data are drawn from the BIBB/IAB Strukturerhebung 1991/92.
The dependent variables are 4-point Lickert scales on 4 job satisfaction dimensions.
Adjusted standard errors are used. Standard errors under coefficients.
Further controls are education, age, monthly income, working hours
* Denotes significant at 10 percent level.
** Denotes significant at 5 percent level.
*** Denotes significant at 1 percent level.

In addition, we report the first stage coefficient of our instrument and the first stage F-value at the bottom of the table. The coefficient of the first stage is positive, indicating that women who live in a region with more stereotypically male jobs are significantly more likely to choose a stereotypically male job. The first stage F-value is about 9.04. Staiger and Stock (1997) propose an F-value of 10 as rule of thumb for avoiding problems of weak instruments. Our F-value of 9.04 is only slightly below 10. The first row of the table provides the estimates of P_i. The estimation results show the same signs that we obtained in the classical ordered probit estimation of Table 4.7, but the coefficients and standard errors blow up as we estimate P_i with less precision. The only coefficient that remains significant at the 10 percent level is the negative effect on satisfaction with work climate.

Table 4.16 reports the results for men. The z-statistics for θ are 4.17 for overall satisfaction, 2.95 for satisfaction with work climate, 1.81 for satisfaction with contents of tasks and 1.52 for income satisfaction. All values—apart from income satisfaction—indicate that we have to reject the hypothesis that P_i is exogenous under the assumption that our instrument is valid. Moreover, our instruments show the expected direction and our F-statistic is about 13.23—a value above 10. In contrast to the estimates in Table 4.11 where the effect was negative for overall satisfaction and the satisfaction with contents of tasks, all coefficient values of P_i are positive. However, as for women, the effect remains significant only for satisfaction with work climate.

Table 4.16: Job satisfaction and occupational stereotypes: men (2SCML)

Dependent variables:	Overall	Work climate	Tasks	Income
Index: Stereotypes P	3.732	2.64**	1.595	1.475
	(2.51)	(1.301)	(1.274)	(1.006)
Coef. Instrument	0.737***	0.737***	0.737***	0.737***
	(0.203)	(0.203)	(0.203)	(0.203)
z-statistic: θ	4.17	2.95	1.81	1.52
F-statistic: first stage	13.23	13.23	13.23	13.23
N	11660	11660	11660	11660

Note: All data are drawn from the BIBB/IAB Strukturerhebung 1991/92.
The dependent variables are 4-point Lickert scales on 4 job satisfaction dimensions.
Adjusted standard errors are used. Standard errors under coefficients.
Further controls are education, age, monthly income, working hours
* Denotes significant at 10 percent level.
** Denotes significant at 5 percent level.
*** Denotes significant at 1 percent level.

As previously mentioned, our instrumental variable estimation allows us to identify only the LATE for a sub-population of individuals restricted in their job choices because of the industrial structure within their region. We argue that these individuals are less likely to be in their jobs because they particularly favor stereotypically female or male jobs and that they did not choose their jobs because they were especially well prepared to cope with the possible negative effects of gender-specific stereotypes.

4.4.4 Sensitivity analysis

This section provides a sensitivity analysis for different sub-populations of our sample. As already mentioned, the biggest concern in estimating the effect of occupational stereotypes on job satisfaction is that individuals in different jobs are likely to have different characteristics and hold their jobs for different reasons. As a result, occupational stereotypes have different effects on individuals in different jobs. As it is nearly impossible to find an instrument or a natural experiment that induces a random assignment of individuals into their jobs, this section provides a sensitivity analysis in which we examine different sub-samples for which we have information about the individual's job choices. In particular, our data set contains information about individuals who changed their jobs and about the reasons for their job changes.

Tables 4.17 and 4.18 present results for two groups of individuals. The first group contains individuals who changed their jobs to earn more, to perform more interesting tasks, or to have more personal responsibilities. The second group of individuals contains individuals who were displaced or laid off from their old jobs or who suffered health problems and remain at their former jobs. Both groups have their jobs for very different reasons: The first group contains voluntary movers, who are likely to have considered the effects of occupational stereotypes before the job change yet still chosen the job they hold. The second group holds their jobs because they were forced to take that job by an exogenous event. Both groups of individuals are likely to experience the negative or positive effects of stereotyping in fairly different ways. The first group chooses their jobs to improve their working situation and to have a better job. The second group experienced a negative shock and had to change their jobs invuoluntary.

Table 4.17 presents the results for women. The first part presents the results for the voluntary and involuntary movers without controls for unpleasant working conditions. The second part presents the results with such controls. Without controls for unpleasant working conditions, the results for voluntary movers mimic the results for women in Table 4.7, with the negative effect of P_i on overall satisfaction now even significant. When we now control for unpleasant working conditions, the effects become insignificant, apart from the effect for income satisfaction. For women who changed jobs involuntarily, we find positive effects for all specifications—a sharp contrast to the former results. Maybe those women who lost their job and manage to end up in a higher paid male job are more satisfied than those women ending up in a lower paid male job. However, no effect is significantly different from zero, and the sample size is only around 400. The effects are similar whether we control for unpleasant working conditions or not.

Table 4.18 presents the results for men. For voluntary movers and without controls for unpleasant working conditions, we find a negative insignificant effect of P_i on overall satisfaction, a positive but insignificant effect on satisfaction with work climate, a negative significant effect on satisfaction with contents of tasks and a positive significant effect for income satisfaction. If we control for unpleasant working conditions most of the effects—apart from satisfaction with income—turn positive: significant for satisfaction with work climate and income but insignificant for the other two satisfaction categories. For involuntary movers we find no significant effect, and the effect of P_i on work climate is now negative. The effects for the first group of voluntary movers are similar to those in Table 4.11 and Table 4.13. Such as it is the case for women we find no significant effects for involuntary movers and the coefficient signs differ from the former results. One possible explanation is that the negative shock decreased the satisfaction level for all workers to a very low level and does not differ much irrespective of whether the individual is in a stereotype male or female job. Yet we have to interpret the effects with caution as the sample size is rather small.

Table 4.17: Job satisfaction and occupational stereotypes: women (job movers)

Voluntary movers				
Dependent variables:	Overall	Work climate	Tasks	Income
Without controls				
Index: Stereotypes *P*	-0.273**	-0.223*	-0.370***	0.129
	(0.135)	(0.134)	(0.137)	(0.141)
With controls				
Index: Stereotypes *P*	-0.060	-0.065	-0.118	0.233
	(0.146)	(0.150)	(0.144)	(0.148)
Observations:	883	883	883	883
Involuntary movers:				
Dependent variables:	Overall	Work climate	Tasks	Income
Without controls				
Index: Stereotypes *P*	0.195	0.039	0.147	0.220
	(0.205)	(0.188)	(0.188)	(0.205)
With controls				
Index: Stereotypes *P*	0.234	0.080	0.188	0.233
	(0.209)	(0.190)	(0.193)	(0.209)
Observations:	480	480	480	480

Note: All data are drawn from the BIBB/IAB Strukturerhebung 1991/92.
The dependent variables are 4-point Lickert scales on 4 job satisfaction dimensions.
Robust standard errors are used. Standard errors under coefficients.
Regression includes all control variables.
* Denotes significant at 10 percent level.
** Denotes significant at 5 percent level.
*** Denotes significant at 1 percent level.

Table 4.18: Job satisfaction and occupational stereotypes: women (job movers)

Voluntary movers				
Dependent variables:	Overall	Work climate	Tasks	Income
Without controls				
Index: Stereotypes *P*	-0.072	0.038	-0.189**	0.211***
	(0.075)	(0.071)	(0.076)	(0.072)
With controls				
Index: Stereotypes *P*	0.114	0.145*	-0.040	0.277***
	(0.081)	(0.077)	(0.084)	(0.079)
Observations:	2343	2343	2343	2343
Involuntary movers:				
Dependent variables:	Overall	Work climate	Tasks	Income
Without controls				
Index: Stereotypes *P*	-0.063	-0.108	0.100	0.132
	(0.120)	(0.120)	(0.122)	(0.114)
With controls				
Index: Stereotypes *P*	0.024	-0.053	0.177	0.185
	(0.130)	(0.129)	(0.133)	(0.123)
Observations:	882	882	882	882

Note: All data are drawn from the BIBB/IAB Strukturerhebung 1991/92.
The dependent variables are 4-point Lickert scales on 4 job satisfaction dimensions.
Robust standard errors are used. Standard errors under coefficients.
Regression includes all control variables.
* Denotes significant at 10 percent level.
** Denotes significant at 5 percent level.
*** Denotes significant at 1 percent level.

4.5 Conclusion

This paper has provided evidence of an empirical relation between occupational stereotypes and job satisfaction. Women appear less satisfied in stereotypically male occupations than in stereotypically female occupations. This disparity in satisfaction is most pronounced for satisfaction with work climate and satisfaction with the contents of tasks. In contrast, income satisfaction is higher for women in stereotypically male jobs. Meanwhile, men report higher satisfaction values in stereotypically male jobs, in particular with respect to their work climate.

Even if stereotyping is persistent in the labor market and affects the subjective well-being of individuals, classical economic theory does not provide a direct link between occupational stereotypes and job satisfaction. However, as we mentioned in the introduction a recent influential literature incorporating the concept of identity into an economic framework hypothesizes a structural relationship between utility payoffs and different kinds of jobs. Akerlof and Kranton (2000)[7] state that individuals are assigned to different social categories and that these social categories are associated with different attributes and prescribed behaviors. If individuals violate these behaviors, they could suffer identity losses. In contrast, if they behave in line with the prescriptions of their social category, they might gain utility.

As our results show, occupations and tasks are also associated with social gender categories indicating either male or female attributes or behavior, and thus follow such categorical prescriptions. In particular we show that jobs containing tasks such as driving vehicles, maintaining machines, or doing calculations and bookkeeping are more likely to be considered inappropriate for women, whereas tasks such as cleaning, care-giving, or teaching are considered more appropriate for women.

Moreover, the paper shows that occupational stereotypes affect different dimensions of job satisfaction for women and men in different ways. We show that women are less satisfied with their work climate and contents of tasks but are more satisfied with their

[7] The theory of Akerlof and Kranton (2000) is not independent of earlier theories on discrimination, especially by co-workers, such as by Becker (1971).

income in stereotypically male jobs. As these results hold even when we control for working hours, unpleasant working conditions, and income (as well as for different sub-populations), we argue that the negative relationship between job satisfaction and stereotypically male jobs cannot be exclusively explained by women favoring different bundles of work characteristics than men—an explanation brought up by Bender et al. (2005) to explain the gender wage gap. Likewise the theory of Clark (1997) about differences in expectations might not fully explain why women are less satisfied with their work climate in stereotypically male jobs and men are more satisfied with their work climate in stereotypically male jobs. Especially because it is not likely that women (men) have high expectations of a good work climate in male (female) jobs which are disappointed afterwards. Nevertheless, the negative effect of male occupational stereotypes on women's satisfaction with their work climate is robust for a variety of empirical specification, whereas men are more satisfied with their work climate in stereotypically male jobs. We argue that such a relationship is rather in line with Akerlof and Kranton (2000), who argue that deviating from one's social category affects not only one's own sense of self but also the identity of others nearby. Therefore, their theory suggests that women and men should have different feeling about their work climate within stereotypically male or female jobs.

As our results suggest that factors such as prejudice and gender-specific stereotypes affect the utility outcomes of women and men, we argue that social influences other than income and other observable job characteristics (such as, for example, working hours), are very likely to affect individual's choice of a job. Such social influences, however, are very difficult for policy makers to change and might explain the persistence of gender job segregation in Western countries. Moreover, social occupational stereotypes might induce inefficient allocations of workers to jobs and might induce welfare losses.

One potential remedy to overcome the negative consequences of gender specific stereotypes in the labor market might be to introduce quotas for female workers in the occupations. Such quotas might help to reduce such stereotypes as it might be easier for women to integrate in the work process if they have more female colleges.

To sum op throughout this dissertation we have shown that the task-based view helps us to understand a great variety of labor market outcomes. Therefore, the last section summarizes all results, provides policy implications and gives ideas for further research.

Chapter 5

Final Remarks

In an effort to better understand the link between technology and labor demand, recent literature has adopted a task-based view of technological change. The major feature of this framework is conceptualizing work as a series of tasks. However, the relationship between the task-based view and individual careers and labor market outcomes has been less clearly pronounced. This dissertation shows in a series of empirical investigations that the tasks-based view explains different phenomena in the labor market, such as human capital depreciation, gender-specific job choices, or varying income losses after job displacement.

The first research question of this dissertation is whether the task-based view is able to explain why different types of human capital suffer from depreciation in different ways. Therefore, we show in a first step that human capital depreciation matters and affects the income of workers throughout their whole careers. In a second step, we show that the rate at which the worker's human capital depreciates is highly heterogeneous according to the types of tasks workers are charged with. In particular, we identify two classes of tasks with highly different effects on the workers' human capital depreciation. On one hand, we identify the category of knowledge-based tasks—i.e. tasks that are closely related to certain technologies or the general stock of knowledge available to society. On the other hand, we identify experience-based tasks as tasks demanding personal characteristics that can be improved by more and more experience. Experience-based task are not closely attached to a certain kind of technology or the general stock of knowledge. We show that workers mainly performing knowledge-based tasks suffer stronger from human capital depreciation than workers mainly performing experience-based tasks.

In our first contribution, we confirm previous investigations from other countries by providing evidence on human capital depreciation for Germany. Our second contribution introduces the task-based view in the literature on human capital depreciation, by showing that human capital depreciation is highly heterogenous according to the worker bundles of tasks.

From the individual's point of view, the results should affect a worker's decision to invest in human capital. Investing purely in high-technology skills at the beginning of an individual's career could be a risky strategy for an individual, because there is a danger of suffering high rates of human capital depreciation. Workers who invest purely in high technological skills will be outperformed by younger colleagues at later stages of their career—especially, if workers invests too little in ongoing training. A purely technological human capital investment might be beneficial in early career stages but could negatively affect the labor market outcomes (wage losses, unemployment) at later career stages.

From the firm's perspective, the result provides implications about the age and experience distributions of firms in different industries. Remaining with high percentages of younger workers might be an advantageous strategy for firms in technology-intensive industries, whereas firms in sectors demanding rather experience-based tasks might be better off by hiring older and more experienced workers. Moreover, even within a firm, it might be more profitable for younger workers to occupy high-technology jobs and to have older workers occupy non-technical jobs. Obviously apart from human capital depreciation, many other factors influence the optimal age mix of workers within firms. Therefore, we do not suggest to hire only young workers in technical jobs and old workers in non-technical jobs. We only argue that forms of human capital depreciation should be considered in hiring and training decisions.

Our suggestions for further research is to find or construct better data sets that are able to track informations about individuals task bundles over long time periods. With such data sets research would be able to measure changes in demands for certain kinds of tasks and could infer how such changes affect the value of the individuals human capital.

The second part of this dissertation continues investigating the relation between tasks and income. The aim of this part is to investigate income losses of displaced workers performing different types of tasks. Therefore, we introduce the task-based view in the literature on displacement losses. In particular, we investigate displacement losses of young apprenticeship graduates who undertook their apprenticeship training in different occupations. Our evidence shows no significant differences in occupational-specific displacement losses. We attribute this finding to the nature of the Danish apprenticeship system, providing apprentices with up-to-date skills that are easily transferable across occupations. An additional finding of this chapter is that displacement losses increased substantially after a nationwide decentralization of the wage bargaining system in Denmark. Moreover, we can show that displacement losses under a rigid wage bargaining system appear to be fully attributed to spells of non-employment, whereas under a decentralized wage bargaining system wage losses remain substantially—even for the continuously employed.

As a result the contributions of our second part are twofold. First, we contribute to the literature by showing that young apprenticeship graduates do not differ substantially in their displacement losses. A finding that contradicts other studies that find bigger displacement losses for manufacturing workers than for service, or commercial workers (Jacobsen et al.; 1993). Second, we show a strong relation between the flexibility of wages and displacement losses. This gives new insights of why displacement losses differ so substantially between Europe and its mostly rigid wage formation process and the U.S. with its flexible wage bargaining system. Besides investigating occupational-specific displacement losses for young apprenticeship graduates, further research should aim at investigating occupational specific displacement losses for other types of workers such as university graduates or unskilled workers.

The last part of this dissertation investigates whether tasks are linked to gender-specific stereotypes and asks whether the tasks-based view can help to explain gender specific job choices in the labor market. We show that occupational stereotypes cannot be neglected in labor market research. In particular, we find strong gender-specific stereotypes for tasks. Consistent with former literature that incorporates the sociological concept of identity into classical economic models, we argue that our results indicate that occupational stereotypes affect individuals utility outcomes. We find that women, performing stereotypically male tasks, report lower values of satisfaction with their work-climate and contents of tasks but higher satisfaction with their income. In contrast men, performing stereotypically male tasks, report higher job satisfaction values for all satisfaction categories but only if we control for unpleasant working conditions such as night-shifts and heavy lifting. We argue that these results indicate that individuals trade-off their utility losses arising from occupational stereotypes with other job characteristics such as higher income or unpleasant work characteristics. Consequently stereotypes affect the job choice behavior of individuals.

Therefore, our contribution lies in providing the first empirical investigation that shows a link between gender-specific stereotypes and job satisfaction. In this way we contribute to the literature by providing empirical evidence that social factors affect utility outcomes of workers and support recent theoretical papers such that of Akerlof and Kranton (2000). Moreover, we contribute to the literature by providing and supporting a new explanation for the persistence of gender-specific occupational segregation in western countries that differs from classical theories of discrimination or gender-specific preferences (Bender et al.; 2005).

As our results suggest that factors such as prejudices and gender-specific stereotypes affect the utility outcomes of women and men, classical policy interventions that aim at reducing discrimination by anti-discrimination laws might fail miserably. Politician might rather aim at early educational policies and try to change certain social norms. However, such social influences might be very hard to change and a stable gender job segregation in Western countries might induce inefficient allocations of workers to jobs and induce welfare losses for a country's economy. Therefore, further research should find a way of investigating how stereotypes evolve over time and how such stereotypes induce well-fare losses in the long run.

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